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Bastian, Nathaniel D.

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Maastricht University
School of Business and Economics
Department of Quantitative Economics
P.O. Box 616, 6200 MD Maastricht
The Netherlands

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According to current force health protection policy, the U.S. Army's Health Service Support system is designed to maintain a healthy force and to conserve combat strength of deployed soldiers. Specifically, this system remains particularly effective by employing standardized aeromedical evacuation assets and providing a responsive field-sited medical treatment facility for the wounded soldiers evacuated from the battlefield. Since the beginning of Operation Enduring Freedom, military commanders have faced a significant combinatorial challenge integrating limited air evacuation assets into a fully-functional, comprehensive system for the entire combat theatre. This work describes a robust, multi-criteria decision analysis methodology using a scenario-based, stochastic optimization goal programming model that U.S. Army medical planners can use as a strategic and tactical aeromedical evacuation asset planning tool to help bolster and improve the current air evacuation system in Afghanistan. Specifically, this model optimizes over a set of expected scenarios with stochastically-determined casualty locations to emplace the minimum number of helicopters at each medical treatment facility necessary to maximize the coverage of the theatre-wide casualty demand and the probability of meeting that demand, while minimizing the maximal medical treatment facility evacuation site total vulnerability to enemy attack.

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DEPARTMENT OF QUANTITATIVE ECONOMICS
SCHOOL OF BUSINESS AND ECONOMICS

MAASTRICHT UNIVERSITY

P.O BOX 616, 6200 MD MAASTRICHT, THE NETHERLANDS

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A STRATEGIC APPROACH TO OPTIMIZING THE U.S. ARMY'S AEROMEDICAL EVACUATION SYSTEM IN AFGHANISTAN

by

Nathaniel D. Bastian
I544590

July 10, 2009

Thesis Advisor: Alexander Grigoriev
Second Reader: Tjark Vredeveld

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A STRATEGIC APPROACH TO OPTIMIZING THE U.S. ARMY'S AEROMEDICAL EVACUATION SYSTEM IN AFGHANISTAN

Nathaniel D. Bastian
Second Lieutenant, United States Army
B.S., United States Military Academy at West Point, 2008

Submitted in partial fulfillment of the
requirements for the degree of

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DEPARTMENT OF QUANTITATIVE ECONOMICS
SCHOOL OF BUSINESS AND ECONOMICS
MAASTRICHT UNIVERSITY

July 10, 2009

Author: Nathaniel D. Bastian

Approved by: Professor Alexander Grigoriev, Ph.D.
Thesis Advisor, Department of Quantitative Economics

Professor Tjark Vredeveld, Ph.D.
Second Reader, Department of Quantitative Economics

Professor Dr. Jean-Pierre Urbain, Ph.D.
Chairman, Department of Quantitative Economics

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ABSTRACT

According to current force health protection policy, the U.S. Army's Health Service Support system is designed to maintain a healthy force and to conserve combat strength of deployed soldiers. Specifically, this system remains particularly effective by employing standardized aeromedical evacuation assets and providing a responsive field-sited medical treatment facility for the wounded soldiers evacuated from the battlefield. Since the beginning of Operation Enduring Freedom, military commanders have faced a significant combinatorial challenge integrating limited air evacuation assets into a fully-functional, comprehensive system for the entire combat theatre. This work describes a robust, multi-criteria decision analysis methodology using a scenario-based, stochastic optimization goal programming model that U.S. Army medical planners can use as a strategic and tactical aeromedical evacuation asset planning tool to help bolster and improve the current air evacuation system in Afghanistan. Specifically, this model optimizes over a set of expected scenarios with stochastically-determined casualty locations to emplace the minimum number of helicopters at each medical treatment facility necessary to maximize the coverage of the theatre-wide casualty demand and the probability of meeting that demand, while minimizing the maximal medical treatment facility evacuation site total vulnerability to enemy attack.

Key Words: Goal Programming, Optimization, Stochastic Modeling, Decision Analysis, Medical Evacuation

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

GLOSSARY OF TERMS

AAR	After Action Review
AO	Areas of Operation
BCT	Brigade Combat Teams
CAA	Center for Army Analysis
CASS	Center for Army Medical Department Strategic Studies
CENTCOM	Central Command
CSTC-A	Combined Security Transition Command – Afghanistan
DoD	Department of Defense
DOE	Design of Experiments
GAMS	General Algebraic Modeling System
HSS	Health Service Support System
ISAF	International Security Assistance Force
MEDEVAC	Aeromedical Evacuation System
MTF	Medical Treatment Facility
NATO	North Atlantic Treaty Organization
OEF	Operation Enduring Freedom
WIA	Wounded-in-Action

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The Soldier's Creed

I am an American Soldier.

I am a Warrior and member of a team.

I serve the people of the United States and live the Army Values.

I will always place the mission first.

I will never accept defeat.

I will never quit.

I will never leave a fallen comrade.

I am disciplined, physically and mentally tough, trained and proficient in my warrior tasks and drills.

I always maintain my arms, my equipment and myself.

I am an expert and I am a professional.

I stand ready to deploy, engage, and destroy the enemies of the United States of America in close combat.

I am guardian of freedom and the American way of life.

I am an American Soldier.

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1 INTRODUCTION

1.1 BACKGROUND

The United States Army is making remarkable strides in its systematic approach to delivering health care across a continuum of combat operations. According to current force health protection policy, the U.S. Army's Health Service Support (HSS) system is designed to maintain a healthy force and to conserve combat strength of deployed soldiers. Specifically, the HSS system remains particularly effective by providing prompt medical treatment to prepare patients for evacuation, employing standardized air and ground medical evacuation assets, providing a responsive field hospital for the wounded soldiers evacuated from the battlefield, and providing various other health and preventive medicine services. Furthermore, the HSS system incorporates the maximum use of emerging technology to improve battlefield survivability (see Army Field Manual 4-02).

Although more wounded soldiers survive compared to any other war because of the HSS system, the U.S. Army can still greatly improve its systematic approach to treat and evacuate casualties from combat zones. As a pillar of military medical doctrine, optimizing the emplacement of medical treatment and aeromedical evacuation (MEDEVAC) assets can increase casualty survivability given a set of resource constraints. Therefore, thorough investigation and development of improved analytical solutions derived from objectives concerning casualty coverage, resource utilization and vulnerability measures directly supports the military medical mission.

Since the beginning of Operation Enduring Freedom (OEF) in Afghanistan, military commanders have faced a significant challenge integrating coalition medical assets into a fully-functional, interconnected HSS system for the entire OEF theatre. In 2006, OEF battlefield responsibilities transitioned from a U.S. military command to a North Atlantic Treaty Organization (NATO) military command. As per this changeover of command, the Combined Security Transition Command – Afghanistan (CSTC-A) desired an integration of limited MEDEVAC assets from each contributing NATO country into a comprehensive MEDEVAC system. Moreover, CSTC-A faced an immense combinatorial problem given the number of potential MEDEVAC helicopter locations, the number of different aircraft models for employment and its associated constraints, the potential sites for casualty sustainment, and the number of supporting Medical Treatment Facility (MTF) locations.

1.2 PROBLEM DEFINITION

CSTC-A and the Central Command (CENTCOM) requested an analytical methodology to tackle the following problem:

Given a distribution of MEDEVAC missions, where do coalition forces position several different model types of helicopters amongst various possible locations to minimize the time from injury occurrence to arrival at a MTF? Given that positioning, what percent of MEDEVAC missions can be supported in less than or equal to two hours from the time of soldier injury to arrival and patient drop-off at the closest MTF site?

Zeto et al. (2006) at the U.S. Army Center for Army Analysis (CAA) first tackled this problem by developing the following research questions:

1. *What locations constitute the subset of the possible locations at which helicopters should be emplaced?*
2. *For each selected location, what model aircraft should be emplaced at each?*
3. *How many aircraft should be emplaced at each selected location?*

From these research questions, CAA’s analysts developed a methodology consisting of a multivariate hierarchical cluster analysis, a Monte Carlo simulation, and a dual-criteria goal program. Also, Fulton et al. (2009) at the U.S. Army Center for Army Medical Department Strategic Studies (CASS) developed a different methodology to tackle a similar problem concerning medical evacuation and mobile hospital asset planning for steady-state combat operations in Iraq. Following examination of the analysis results from both CAA and CASS, several areas for model extension and further analytical investigation arose.

1.2.1. MOTIVATION

Therefore, this work serves as a combination and extension of the analysis methodologies performed by CAA and CASS. First, we expand the goal program to account for MTF site vulnerability associated with the amount of enemy activity per Afghan province where MEDEVAC operations are conducted to and from each MTF evacuation site, and we incorporate goal priority weights into the modeling objective. A second area of motivation involves reformulating the model to account for future uncertainty by optimizing over a set of expected scenarios based on specific Design of Experiments (DOE) factors, making the model robust and keen for both strategic and tactical MEDEVAC asset planning and decision-making. Third, we use a multi-stage stochastic modeling approach that first determines the casualty demand locations and respective monthly casualty demand, and then we execute the second-stage of the model based on the first decision; we also modify the original data parameters to account for stochastic effects. Fourth, we expand the model by integrating a multi-use, decision-analysis tool with statistical analyses of the modeling results in order to assist the user in his or her decision-making process. A fifth area of motivation concerns developing a model with a high level of variety constraint aggregation allowing computationally fast solutions – the modeling tractability goal is find an optimal solution within one minutes – which is especially important to use the model as a decision-making instrument for tactical MEDEVAC asset planning. Last, we develop a three-dimensional shortest helicopter path algorithm to more accurately compute the probability of successfully evacuating patients from a casualty demand location to the closest MTF site within two hours. In order to determine the optimal flight route and respective helicopter flight time, this algorithm considers the effects of terrain obstacles, known enemy locations, air traffic control regulations, limitations due to patients' pulmonary conditions, helicopter performance at high altitudes, and the dependence of helicopter velocity on density altitude.

1.2.2 PURPOSE

Therefore, this work describes a robust, multi-criteria decision analysis methodology using a scenario-based, stochastic optimization goal programming model that U.S. Army medical planners can use as a strategic and tactical MEDEVAC asset planning tool to help bolster and improve the current HSS system within Afghanistan to support OEF. Specifically, this model optimizes over a set of expected scenarios to determine the optimal emplacement of MEDEVAC assets (including MEDEVAC helicopter sites and the type and quantity of aircraft at each site) in Afghanistan based on stochastically-determined casualty locations and three optimization goal criterion: maximize the aggregate expected casualty demand coverage, minimize MEDEVAC helicopter spare capacities, and minimize the value of the maximal MTF evacuation site total vulnerability to enemy attack.

1.2.3 COMPLEXITY

This problem falls under the category of discrete facility location modeling, where demands arise on distinct nodes and the facilities are restricted to a finite set of candidate locations (Daskin 2008). Here, this problem classifies as a covering-based model because there is a coverage time (two hours) within which casualties (at specific casualty demand nodes) must be evacuated in order to be considered covered. Furthermore, Daskin (2008) suggests three prototypical problems under the class of covering models: the set covering model, the maximal covering model, and the *p*-center model. Although some instances these problems can be solved in polynomial time using mixed integer programming techniques where the linear programming relaxation is an integer solution, each of these covering-based models is classified as *NP*-hard (Daskin 2008). With this in mind, this MEDEVAC asset optimization problem also classifies as *NP*-hard as it falls under the class of discrete location coverage modeling.

The next section presents a concise yet substantive literature review particularly concerning emergency service vehicle and facility location optimization problems that have been researched and tackled using various solution methodologies over the past few decades.

1.3 LITERATURE REVIEW

One of the first attempts to solve the problem concerning the location of emergency service facilities was considered by Toregas et al. (1971), who used linear programming solution techniques for a location set covering problem with equal objective costs. Berlin & Liebman (1974) solve an emergency ambulance location problem by systematically combining a location set covering model with a discrete event simulation, which simultaneously solves the facility location and vehicle allocation problems. Geoffrion & Graves (1974) develop a solution technique based on Benders decomposition to solve a multi-commodity capacitated, single-period distribution system problem formulated as a mixed integer linear program. Larson (1975) presents an approximation procedure using multiple server queuing theory to analyze a number of resource allocation problems in urban emergency service systems. Aly & White (1978) develop a probabilistic formulation of the emergency service location problem as an extension to the location set covering problem to account for the assumption that the location of an incident is a random variable occurring uniformly over a certain area.

In addition to the solution methods proposed above, goal programming is a modeling technique used to analyze problems involving multiple, conflicting objectives (Ignizio 1978). Charnes & Storbeck (1980) apply location covering techniques within a goal programming framework to develop a method for the positioning of multilevel emergency health service systems so that each service level maximizes coverage of its own demand population and there is assurance of backup coordination between levels. Daskin (1983) presents an integer programming formulation for the maximum expected covering location problem, which he solves using a heuristic solution algorithm. Gass (1986) tackles a military personnel planning problem using goal programming, where he presents a process to establish goal priorities and objective function weights. Neebe (1988) considers the problem of locating emergency service facilities, where he presents a linear programming relaxation procedure to determine the minimal number of required facilities given that the maximum distance between the demand points and their nearest facility does not exceed some specified value. Pirkul & Schilling (1988) design an effective solution procedure using a Lagrangian relaxation of a model formulation for emergency service systems where facility workload is controlled and backup service for some or all demand points is considered. ReVelle & Hogan (1989) derive two new model formulations from the probabilistic location set covering problem to incorporate the dynamic aspect into emergency facility and vehicle location decisions. They propose the maximum reliability location problem and the α-reliable *p*-center problem.

Batta & Mannur (1990) propose a modeling framework combining the set covering and maximal covering location problems to locate emergency vehicles in an environment requiring multiple response units. Pirkul & Schilling (1991) present an efficient solution combining Lagrangian relaxation and subgradient optimization procedures to solve an extended capacitated maximal covering location problem. Ball & Lin (1993) derive a reliability-based binary integer programming optimization model for emergency service planners to solve the strategic problem of where to locate emergency service stations and the tactical problem of the number of vehicles to place at each station. ReVelle & Marianov (1996) extend the probabilistic version of the maximal covering location problem by developing a more realistic model for emergency systems known as the queuing maximal availability location problem. The model emplaces a limited number of emergency vehicles in order to maximize the calls for service using a queuing theory model for server availability. Gendreau et al. (1997) designs a tabu search metaheuristic to solve a double coverage location model for ambulance services with an embedded decision support system to assist real-time vehicle redeployment operations.

Marianov & Taborga (2001) expand the maximal covering location model into the economic market realm, where they present a model and heuristic solution approach for the optimal location of competitive public health care centers. In recent years, researchers and analysts have focused on developing more probabilistic approaches to logistics problems. For instance, Santoso et al. (2005) present a stochastic programming approach for supply chain network design with a large number of scenarios for the uncertain problem parameters. For their solution methodology, they integrate a sample average approximation scheme with a Benders decomposition algorithm. Jia et al. (2005) propose a general facility location model for large-scale emergencies, such as earthquakes and terrorist attacks, that can be cast as a generalization of the covering, *p*-median, and *p*-center models that have been developed for regular emergency services facility location. Alsalloum & Rand (2006) suggest a goal programming approach to solving the problem of identifying the optimal locations of a pre-specified number of emergency medical service stations, which is an extension to the maximal covering location problem. Moreover, modeling techniques have been researched and proposed for military facility vulnerability analysis. For example, Brown et al. (2006) apply attacker-defender, bilevel and trilevel optimization models to help the military assess facility vulnerability when faced with an intelligent enemy, such as terrorists. Gong & Batta (2007) propose an ambulance allocation model for post-disaster rescue operations, where they initially focus on allocating the correct number of ambulances to each casualty cluster, and then analyze the ambulance reallocation problem to redistribute ambulances for full utilization. Silva & Serra (2008) tackle a problem concerning emergency services in urban settings where service calls involving danger to human life require higher priority compared to more routine situations; they formulate a covering model that considers different priority levels. Related to modeling for military medical planning, Fulton et al. (2009) propose a two-stage stochastic optimization model for the relocation of deployable military hospitals, the reallocation of hospital beds and commensurate staff, and the emplacement of tactical evacuation assets during steady-state military combat operations.

1.4 APPROACH

The remainder of this work describes our strategic approach to optimizing the U.S. Army's aeromedical evacuation system in Afghanistan, which is organized as follows. Section 2 explains our theoretical methods used, particularly the optimization methodologies incorporated into the model, the mixed integer programming formulations, and our three-dimensional shortest helicopter path algorithm. Section 3 discusses our modeling experiment, specifically explaining the Afghanistan MEDEVAC asset optimization context, model data parameter quantification and assumptions, model implementation and solutions, and the final results and sensitivity analyses useful for the decision-maker. Concluding remarks, model limitations and areas for further research, and acknowledgments are presented in Section 4.

2 THEORETICAL METHODS

2.1 MODELING METHODOLOGIES

The following modeling techniques are incorporated in this robust, multi-criteria, decision-analysis methodology to tackle the Afghanistan MEDEVAC asset optimization problem.

2.1.1 GOAL PROGRAMMING

Goal programming is a traditional multi-criteria decision analysis technique that provides an analytical framework through which decision-makers can systematically explore and examine different optimization problem alternatives. Moreover, the decision-maker defines goals for the different optimization objectives considered and evaluates the effects each of these criterion have on the overall optimal solution for the system (Durbach & Stewart 2003). This methodology is particularly useful for strategic planning when incorporated with goal priority weights determined by the decision-maker. In the following solution methodology, our goal programming model consists of three different criteria seeking to maximize the aggregate expected casualty demand coverage while minimizing both MEDEVAC helicopter spare capacities and the maximal medical treatment facility evacuation site total vulnerability.

2.1.2 SCENARIO PLANNING

Scenario planning methods take into account future uncertainty and randomness involved in strategic decision-making. These scenarios are developed in an approach that focuses on underlying factors causing uncertainty within the system. Specifically, this approach aims to identify robust alternatives over the set of probabilistic scenarios (Durbach & Stewart 2003). Design of Experiments (DOE) is a mathematical process used for identifying these different modeling alternatives, as it provides solution designers with a systematic method for modeling the interactive effects of various experimental design factors. Models designed using DOE are called 2^f factorial designs, where f refers to the number of factors considered in each scenario (West 2008). In the following solution methodology, a 2^3 design scenario-approach is utilized to capture uncertainty for better decision-making; the specific scenario DOE factors are discussed in Section 2.2.7. Additionally, the model provides sufficient statistical analyses for each solution found across the given set of scenarios.

2.1.3 STOCHASTIC OPTIMIZATION

Stochastic optimization methods incorporate random elements into the model objective function, model constraints and/or model data parameters, which serve a similar function as scenario planning to aid decision-makers when optimizing in the presence of uncertainty. Furthermore, stochastic programming is frequently used to model both multi-stage optimization problems – where decisions are made periodically based on currently known realizations of some of the random variables – and probabilistic scenario-based problems (Kleywegt & Shapiro 2000). The following solution methodology describes a two-stage stochastic optimization goal program – where the first stage stochastically determines the casualty demand locations and the second stage decides where to emplace MEDEVAC helicopters at a subset of the feasible MTF evacuation sites based on these now known demand sites – that optimizes the expected value of the objective function (i.e. minimizes over a set of probabilistic scenarios), and many of the model data parameters are quantified using stochastic calculations rather than deterministic (see Section 3.2 for more details).

2.2 MODEL DEVELOPMENT

The following goal programming model optimizes over a set of expected scenarios generated from different experimental design factors, providing a robust, multi-criteria decision-analysis mechanism to tackle the Afghanistan MEDEVAC optimization problem. The following sets, data parameters and decisions variables are defined to formulate the model.

2.2.1 SETS

W = experimental design scenarios for evaluation with index $w \in W$

I = monthly casualty demand locations with index $i \in I$

J = feasible MTF sites for helicopter emplacement with index $j \in J$

K = aircraft model types with index $k \in K$

S = number of aircraft to be co-located at MTF evacuation site j with index $s \in S$

G = goals/criteria considered in the goal program with index $g \in G$

T = number of Monte Carlo simulation trials, not in the formulation, with index $t \in T$

2.2.2 DATA PARAMETERS

a_{iw} = the proportion of monthly demand originating at casualty site i such that the summation of a_{iw} for all i equals 1 in each scenario w

P_{ijkw} the probability of successfully evacuating patients from casualty location i to MTF site j with aircraft type k in scenario w within two hours, where MEDEVAC assets are co-located with and dispatched from the closest MTF evacuation site

r_{jksw} = the maximum number of casualties that can be supported from MTF evacuation site j with s number of aircraft type k in scenario w

λ_{iw} = the actual monthly casualty demand emanating from casualty location i in each scenario w

c_k = the number of aircraft of model type k available in OEF theatre

v_{jw} = the vulnerability associated with each MEDEVAC route in/out of each MTF site j in scenario w

vc_{jw} = the total vulnerability threshold level for each MTF evacuation site j in scenario w

$occur_w$ = the expected probability that scenario w occurs, in the objective function

pri_{gw} = the priority weight of goal g in scenario w, in the objective function

2.2.3 DECISION VARIABLES

Binary Variables

Y_{ijk} = binary variable for MEDEVAC assets, equals 1 if evacuation from casualty location i with aircraft type k dispatched from MTF site j is equal to or greater than the pre-specified probability and j is the nearest emplaced MTF evacuation site that facilitates evacuation within two hours, or 0 otherwise

X_{jks} = binary variable for positioning of aircraft, equals 1 if s number of aircraft type k are to be considered for positioning at MTF evacuation site j, or 0 otherwise

Positive Variables

$dmiv_{1w}$ = underachievement deviation for Goal 1 in each scenario w

$dplus_{2jkw}$ = overachievement deviation for Goal 2 for each j, k, and w

$dplus_{3w}$ = overachievement deviation for Goal 3 in each scenario w

V = the value of the maximal MTF evacuation site total vulnerability over all scenarios

Q = the value of the maximum expected sum of the weighted goal deviations over all scenarios

2.2.4 MULTI-CRITERIA OPTIMIZATION GOALS

<u>Optimization Goal #1</u>: The first goal seeks to maximize the aggregate expected casualty demands covered, such that each casualty demand location i can be covered by no more than one in-theatre MEDEVAC asset of type k emplaced at MTF evacuation site j:

$$
\begin{aligned}
&Max && \sum_i \sum_j \sum_k a_i P_{ijk} Y_{ijk} \\
&subject\ to && \sum_j \sum_k Y_{ijk} \le 1 \qquad \forall i \\
& && Y_{ijk} \in \{0,1\}
\end{aligned}
$$

<u>Optimization Goal #2</u>: The second goal seeks to minimize the spare capacities of MEDEVAC helicopters for each type k emplaced at each MTF site j ensuring a sufficient level of pre-determined reliability that an aircraft will be available when casualties occur, such that only s number of type k aircraft can be located at each MTF site j, each casualty demand location i can be covered by no more than one in-theatre MEDEVAC asset of type k emplaced at MTF site j, and the total number of helicopters of type k positioned cannot exceed its in-theatre capacity:

$$
\begin{aligned}
&Min && \sum_s r_{jks} X_{jks} - \sum_i \lambda_i Y_{ijk} \qquad \forall\, jk \\
&subject\ to && \sum_s X_{jks} \le 1 \qquad \forall\, jk \\
& && \sum_j \sum_k Y_{ijk} \le 1 \qquad \forall i \\
& && \sum_s \left(s \sum_j X_{jks} \right) \le c_k \qquad \forall k \\
& && X_{jks} \in \{0,1\},\ Y_{ijk} \in \{0,1\}
\end{aligned}
$$

<u>Optimization Goal #3</u>: The third goal seeks to minimize the value of the maximal MTF evacuation site total vulnerability, such that the total vulnerability of each MTF site j does not exceed its pre-decided enemy vulnerability threshold level, each casualty demand location i can be covered by no more than one in-theatre MEDEVAC asset of type k emplaced at MTF site j, and the value of maximal vulnerability V is greater than or equal to the total vulnerability of the MTF site j with the highest total vulnerability:

$$
\begin{aligned}
&Min && V \\
&subject\ to && \sum_i \sum_k v_j Y_{ijk} \le vc_j \qquad \forall j \\
& && \sum_j \sum_k Y_{ijk} \le 1 \qquad \forall i \\
& && V \ge \sum_i \sum_k v_j Y_{ijk} \qquad \forall j \\
& && Y_{ijk} \in \{0,1\},\quad V \ge 0
\end{aligned}
$$

2.2.5 MIXED INTEGER PROGRAMMING MODEL FORMULATIONS

Model Formulation #1: The first model formulation combines the three optimization goals into a super goal program that optimizes over a set of expected scenarios:

$$Min \quad \sum_{w} occur_{w}\left(pri_{1w}dmiv_{1w} + pri_{2w}\sum_{j}\sum_{k} dplus_{2jkw} + pri_{3w}dplus_{3w} \right) \qquad (1)$$

$$subject\ to \quad \sum_{i}\sum_{j}\sum_{k} a_{iw}P_{ijkw}Y_{ijk} + dmiv_{1w} = 1 \qquad \forall w \qquad (2)$$

$$\sum_{j}\sum_{k} Y_{ijk} \le 1 \qquad \forall i \qquad (3)$$

$$\sum_{s} r_{jksw}X_{jks} - \sum_{i} \lambda_{iw}Y_{ijk} - dplus_{2jkw} = 0 \qquad \forall jkw \qquad (4)$$

$$\sum_{s} X_{jks} \le 1 \qquad \forall jk \qquad (5)$$

$$\sum_{s}\left(s\sum_{j} X_{jks} \right) \le c_{k} \qquad \forall k \qquad (6)$$

$$V - dplus_{3w} = 0 \qquad \forall w \qquad (7)$$

$$\sum_{i}\sum_{k} v_{jw}Y_{ijk} \le vc_{jw} \qquad \forall jw \qquad (8)$$

$$V \ge \sum_{w}\sum_{i}\sum_{k} v_{jw}Y_{ijk} \qquad \forall j \qquad (9)$$

$$X_{jks} \in \{0,1\},\ Y_{ijk} \in \{0,1\} \qquad \forall ijks \qquad (10)$$

$$V,\ dmiv_{1w},\ dplus_{2jkw},\ dplus_{3w} \ge 0 \qquad \forall jkw \qquad (11)$$

The objective function here in (1) seeks to minimize over the set of scenarios the expected sum of the weighted goal deviations. Constraints (2), (4) and (7) refer to the objective functions of each of the three original optimization goals with their respective under/over achievement deviations from their desired goal target values. Constraints (3) suggest that each casualty demand location can be covered by no more than one in-theatre MEDEVAC asset of a certain type emplaced at a MTF evacuation site. Constraints (5) mean that only s number of an aircraft can be located at each MTF site, and constraints (6) dictate that the total number of helicopters of each type positioned cannot exceed its in-theatre capacity. Furthermore, constraints (8) ensure that the total vulnerability of each MTF site does not exceed the pre-decided enemy vulnerability threshold level, and constraints (9) define the value of maximal vulnerability V as greater than or equal to the total vulnerability of the MTF site with the highest total vulnerability over all scenarios. Last, constraints (10) and (11) refer to the binary and positive decision variables, respectively.

<u>Model Formulation #2</u>: The second model formulation also combines the three optimization goal into a super goal program but with a different objective than the previous formulation:

$$\mathit{Min} \qquad Q \tag{12}$$

$$\mathit{subject\ to} \quad Q \ge occur_w \left(pri_{1w} dmiv_{1w} + pri_{2w} \sum_j \sum_k dplus_{2jkw} + pri_{3w} dplus_{3w} \right) \quad \forall\, w \tag{13}$$

$$\sum_i \sum_j \sum_k a_{iw} P_{ijkw} Y_{ijk} + dmiv_{1w} = 1 \qquad \forall\, w \tag{14}$$

$$\sum_j \sum_k Y_{ijk} \le 1 \qquad \forall\, i \tag{15}$$

$$\sum_s r_{jksw} X_{jks} - \sum_i \lambda_{iw} Y_{ijk} - dplus_{2jkw} = 0 \qquad \forall\, jkw \tag{16}$$

$$\sum_s X_{jks} \le 1 \qquad \forall\, jk \tag{17}$$

$$\sum_s \left(s \sum_j X_{jks} \right) \le c_k \qquad \forall\, k \tag{18}$$

$$V - dplus_{3w} = 0 \qquad \forall\, w \tag{19}$$

$$\sum_i \sum_k v_{jw} Y_{ijk} \le vc_{jw} \qquad \forall\, jw \tag{20}$$

$$V \ge \sum_w \sum_i \sum_k v_{jw} Y_{ijk} \qquad \forall\, j \tag{21}$$

$$X_{jks} \in \{0,1\},\ Y_{ijk} \in \{0,1\} \qquad \forall\, ijks \tag{22}$$

$$Q, V,\ dmiv_{1w},\ dplus_{2jkw},\ dplus_{3w} \ge 0 \qquad \forall\, jkw \tag{23}$$

The objective function above in (12) seeks to minimize Q, where constraints (13) define the value of Q as greater than or equal to the maximum expected sum of the weighted goal deviations over all scenarios – a min-max objective function. Constraints (14), (16) and (19) refer to the objective functions of each of the three original optimization goals with their respective under/over achievement deviations from their desired goal target values. Constraints (15) suggest that each casualty demand location can be covered by no more than one in-theatre MEDEVAC asset of a certain type emplaced at a MTF evacuation site. Constraints (17) mean that only s number of an aircraft can be located at each MTF site, and constraints (18) dictate that the total number of helicopters of each type positioned cannot exceed its in-theatre capacity. Also, constraints (20) ensure that the total vulnerability of each MTF site does not exceed the pre-decided enemy vulnerability threshold level, and constraints (21) define the value of maximal vulnerability V as greater than or equal to the total vulnerability of the MTF site with the highest total vulnerability over all scenarios. Last, constraints (22) and (23) refer to the binary and positive decision variables, respectively.

2.2.6 ADDITIONAL DATA PARAMETERS

$dist\_pu_{ijkw}$ = Euclidean distance between casualty site i and MTF evacuation site j to pickup (and drop-off) patients with aircraft k in scenario w

mag_{iw} = radius around AO 'Hotbed' for which casualties are likely to occur in scenario w

o_k = fleet operational readiness for aircraft model k

lit_k = number of patient litters available in aircraft type k

cas_d_w = parameter used to calculate total demand of all casualty locations in scenario w

$evac\_time_{ijkw}$ = Monte Carlo simulation average MEDEVAC time for casualties at i to/from j in scenario w

en_attack_j = enemy capability lethality factor per MTF evacuation site j

vel_{ijkwt} = helicopter transport velocity in trial t between MTF evacuation site j and casualty location i with aircraft k in scenario w

$leth_{iw}$ = lethality multiplier used to model enemy capability uncertainty in scenario w

$trial_{ijkwt}$ = MEDEVAC time per Monte Carlo simulation trial t in scenario w

$time\_inj_{ijkwt}$ = time in trial t from injury at the casualty demand location to notification of supporting MEDEVAC helicopter in scenario w

$time\_wup_{ijkwt}$ = time in trial t from notification to wheels up in scenario w

$time\_pup_{ijkwt}$ = flight time in trial t from closest MTF to pickup casualty in scenario w

$time\_ld_{ijkwt}$ = patient load time in trial t at pickup location in scenario w

$time\_drop_{ijkwt}$ = flight time in trial t from casualty site to closest MTF in scenario w

$time\_offld_{ijkwt}$ = patient off-load time at the MTF in trial t and scenario w

2.2.7 MODELING SCENARIOS

This work uses the DOE mechanism for determining the optimization modeling scenarios. Specifically, the solution methodology has a 2^3 design, which means three different design factors are explored to generate eight different modeling scenarios. These scenario design factors consist of the goal priority weights (pri_{1w}, pri_{2w} & pri_{3w}), the maximum AO 'hotbed' casualty radius (mag_{iw}), and the total vulnerability threshold level for each MTF evacuation site (vc_{jw}). Additionally, although not one of the specific design factors, each scenario has a respective expected probability of occurrence ($occur_w$) set by the decision-maker.

2.3 THREE-DIMENSIONAL SHORTEST HELO-PATH ALGORITHM

The algorithm presented in this section computes a nearly-optimal (i.e. almost fastest) helicopter flight route with respective flight time between an origin (eg. MTF evacuation site) and a destination (eg. casualty demand location), which considers the effects of:

(1) Terrain obstacles within the operating environment
(2) Known enemy hotspots
(3) Air traffic control regulations
(4) Limitations due to patients' pulmonary conditions
(5) Helicopter performance at high altitudes
(6) Dependency of the helicopter velocity on density altitude

2.3.1 ALGORITHM CONDITIONS

Before diving into the specifics of our algorithm, it is important to describe some of the conditions affecting a real-world, nearly-optimal helicopter path during combat operations. Condition (1) is important when determining a helicopter flight route in the three-dimensional space where helicopters must fly over, around or between terrain obstacles such as mountains, which is particularly important in an operating environment such as Afghanistan. Condition (2) is necessary so that helicopters avoid probable enemy attacks during the flight route, thereby safely transporting soldiers and evacuating those WIA casualties requiring medical assistance at the closest MTF site. Condition (3) is essential because there are some flight routes where helicopters are not allowed to fly, such as flying over field artillery and mortar units or other "No Fly" zones. Additionally, there are some flight routes that air traffic controllers' deem un-flyable due to frequently poor weather in terms of visibility and cloud ceiling conditions. Condition (4) is vital such that WIA soldiers suffering from cardiac arrests or other pulmonary injuries cannot fly over 10,000 feet, where patients do not receive oxygen supplements at the higher altitudes. These first four conditions are utilized during the preprocessing phase of our algorithm to determine if the three-dimensional flight route is feasible, where the final two conditions greatly impact the actual helicopter flight time.

Condition (5) suggests that the helicopter performance at high altitudes– assuming that the helicopter engine and all components are operating satisfactorily – is heavily influenced by the density altitude, gross weight, and wind velocity during takeoff, hovering and landing. Gross weight is the only factor that the pilot of the helicopter can control (i.e. changing fuel amounts, number of passengers, or baggage loads). If a helicopter must fly over a mountain against the violent wind downdrafts (although this creates an easy target for the enemy with a silhouette of the helicopter in the sky), it is advisable for a pilot to allow extra distance to safely clear the mountainous terrain. Additionally, there are distinct helicopter airspeed limitations such that as the altitude increases, the never-exceed airspeed (V_{ne}) for most helicopters decreases. For example, at sea level V_{ne} is 86 miles per hour (MPH); at 6,000 feet and 2500 rotor blade rotations per minute (RPM), it is 65 MPH; and at 6,000 feet and 2700-2900 RPM, it is 78 MPH. Above 2,000 feet, V_{ne} decreases 3 MPH per 1,000 feet, and above 6,000 feet, V_{ne} decreases 5 MPH per 1,000 feet. Figure 1 (left) depicts these airspeed limitations due to changes in altitude. Therefore, as the density altitude, gross weight and/or wind velocity increases, the helicopter performance diminishes as well.

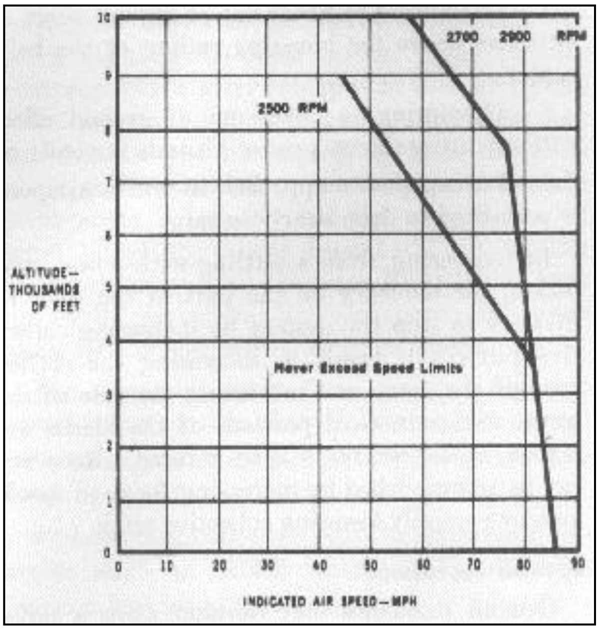

Figure 1: Helicopter Airspeed Limitations

Lastly, condition (6) is also important for the actual flight time calculation where helicopter velocity depends on density altitude. Particularly, as the density altitude increases during flight then the greater the velocity decrement (i.e. decrease in the rate of climb) for any helicopter. The four factors affecting density altitude within the operating environment include the elevation, atmospheric pressure, temperature, and moisture content of the air. As elevation increases, the atmospheric pressure decreases, the air becomes less dense, which increases the density altitude. Figure 2 (right) depicts a chart used to determine density altitude based on the temperature and the pressure altitude, where the pressure altitude is read directly from the altimeter in the cockpit when adjusted to a certain

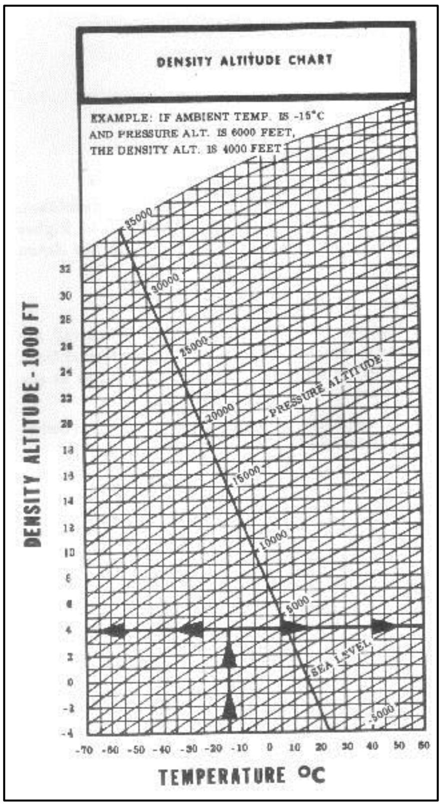

Figure 2: Density Altitude Chart

atmospheric pressure (such as 29.92 inches of mercury). Great changes in temperature cause major changes in air density, even when elevation and pressure remain constant. Therefore, as temperature increases, the air becomes less dense and the density altitude increases. Although the density altitude chart in Figure 2 does not consider the moisture content of the air, increases in air moisture leads to less dense air and, thus, a greater density altitude, when temperature and pressure are constant. Moreover, as the temperature increases, the air can hold a greater amount of moisture. Therefore, the actual density altitude could be much higher then what is computed in Figure 2 if the air contains high moisture content. After computing the density altitude for the temperature and pressure altitude conditions using the density altitude chart, pilots use Figure 3 (left) to compute the helicopter rate of climb and best rate of climb speed. This velocity decrement as density altitude increases is essential for calculating the helicopter flight time in our algorithm (see *Basic Helicopter Handbook*).

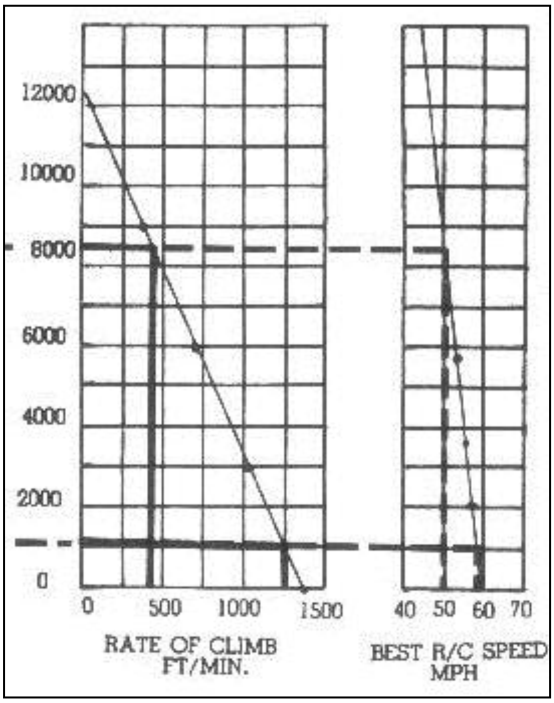

Figure 3: Rate of Climb and Best Rate of Climb Speed Chart

2.3.2 ALGORITHM DESCRIPTION

We use an approximate dynamic programming algorithm to solve the three-dimensional fastest helicopter-path problem. Here, 'approximate' regards the fact that the originally continuous problem is discretized. Due to this discretization, the algorithm does not return an optimal solution to the continuous problem but a solution of the flight time at most α times the continuous optimum. The discretization is made in a straight forward way: instead of the continuous operating scene in three-dimensional space, we only consider integer points in some parallelepiped that approximates the operating scene. More specifically, if the operating scene is defined in R_+^3 with $0 \leq x \leq X,\ 0 \leq y \leq Y,\ 0 \leq z \leq Z$, we take into consideration only the integer points in this parallelepiped $S = Z_+^3 \cap \{(x, y, z) \in\ R_+^3 :\ 0 \leq x \leq X,\ 0 \leq y \leq Y,\ 0 \leq z \leq Z\}$. Further, we assume that the helicopter flies only piece-wise linearly from point to point in S. Deviation from the optimal continuous curve defines the multiplicative error of the discrete solution. On the other hand, any continuous partially-differentiable curve in three-dimensional space can be approximated by a piece-wise linear curve with arbitrary precision. Therefore, making the discretization scale dense enough, we can achieve $\alpha \leq 1 + \varepsilon$ for any given $\varepsilon > 0$.

Given two points $p = (x, y, z) \in S$ and $p' = (x', y', z') \in S$, the helicopter flight time between p and p' is defined as follows:

(1.1) $$f(p,p') = \frac{d(p,p')}{|z-z'|}\left|\int_{z}^{z'} \frac{d\,h}{v_0 - h\cdot c}\right| = d(p,p')\left|\frac{\ln(v_0 - zc) - \ln(v_0 - z'c)}{(zc - z'c)}\right|,$$

where $d(p,p')$ is the Euclidean distance (nautical-miles) between p and p', v_0 is the flight speed of the helicopter at sea level (nautical-miles per hour), and *c* is the helicopter speed decrement of the density altitude (from Figure 3, where the necessary density altitude conversions are made depending on elevation, atmospheric pressure and temperature factors).

In the preprocessing phase of the algorithm, for any two points p and p' from *S*, we compute $f(p,p')$ using Equation 1.1. Moreover, for any two points p and p' we test whether the straight-line flight route from p to p' satisfies conditions (1) through (4). If the feasibility conditions are not satisfied, we re-define $f(p,p') = +\infty$. For completeness, we define $f(p,p) = 0$ for any $p \in S$. Now, quadruple (*S*, *F*, *s*, *d*), where $F = \{\, f(p,p') : p, p' \in S\}$, $s, d \in S$, specifies the input of the discrete fastest helicopter-path problem. Here, vertex *s* denotes the origin and vertex *d* denotes the destination of the helicopter flight route.

Let *K* be a clique on the vertex set *S*. Let the length $(p,p') \in E(K)$ be determined by $f(p,p')$. Therefore, it is obvious that the straightforward Dijkstra's dynamic programming algorithm for the shortest *sd*-path in *K* solves the discrete fastest helicopter-path problem.

2.3.3 ALGORITHM PSEUDO-CODE

Again, Dijkstra's dynamic programming algorithm provides an efficient solution to the discrete fastest helicopter-path problem, which repeatedly evolves the front of vertices that are closest (in Euclidean distance) to the origin *s* until the destination vertex *d* is reached.

Rippel et al. (2004) describes Dijkstra's algorithm as follows: the graph is denoted by *G* = (*V*, *E*); the cost function over the edges *E* is represented by *C*; *s* is the origin and *D* is the set of destination vertices. For each vertex *v* ∈ *V*, the algorithm stores an estimate *g*(*v*) of the current cost of the shortest path from the origin. Besides the origin (which is initialized to 0), *g*(*v*) is initialized to $+\infty$. Additionally, his algorithm maintains a set $S \subset V$ of vertices whose final shortest-path values have already been computed, which is initialized with the origin vertex, $\{s\}$, and $g(s) = 0$. This algorithm then recursively selects (or retires) the vertex v in the complement of S that is closest (i.e. shortest Euclidean distance) to the origin. Furthermore, this repetitive process is essentially executed by considering all vertices u that are one-edge neighbors to some vertex v is S, and selecting the vertex v with the smaller cost estimate $g(v) + C(u, v)$. A priority queue within the algorithm – that maintains the best cost estimates so far for all neighbors of S – manages this selection. Therefore, for any vertex u retired to S the algorithm also saves its predecessor vertex v, so that the optimal shortest path may be traced back. The pseudo-code implementation for Dijkstra's algorithm is shown in Figure 4 (below):

```
Dijkstra(G = (V, E), C, s, d)

S = {s}
PriorityQueue = {s}
g(s) = 0
for all v ∈ V\S,
        g(v) = ∞
        predecessor(v) = none
        PriorityQueue.insert(v)

while D ∩ S = ∅,
        v = PriorityQueue.extract_minimum()
        retire v to S
        for u ∈ neighbors(v),
                if (g(u) > g(v) + C(v,u)) then
                        PriorityQueue.decrease_key(u, g(v) + C(v,u))
                        PriorityQueue.predecessor(u) = v

Backtrack from D to s
```

Figure 4: Dijkstra's Dynamic Programming Algorithm

Our three-dimensional shortest helicopter-path algorithm efficiently solves the discrete fastest helicopter-path problem using Dijkstra's algorithm for implementation. Dijkstra's dynamic programming algorithm has a time complexity of $O(n \log n)$, where n represents the number of vertices in V, the number of neighbors for each vertex is bounded, and the priority queue is implemented efficiently using a data structure such as the binary heap (Rippel et al. 2004).

For related algorithms see Dijkstra (1959); Tsitsiklis (1995); Carlyle et al. (2007), Storer and Reif (1994), and Agarwal et al. (1997).

3 EXPERIMENT

3.1 PROBLEM CONTEXT

The following real-world experiment uses our proposed solution methodology to tackle the combinatorial problem defined by CSTC-A and CENTCOM, which specifically concerns optimizing the U.S. Army's aeromedical evacuation system in Afghanistan.

3.1.1 AFGHANISTAN MEDEVAC SYSTEM OPTIMIZATION

Military commanders have faced significant obstacles since the inception of OEF to holistically integrate MEDEVAC assets within Afghanistan to provide a fully-functional HSS system that ensures wounded-in-action (WIA) soldiers are efficiently air evacuated to receive effective medical care at field-sited MTF sites. Figure 5 below depicts Afghanistan with its respective provinces and International Security Assistance Force (ISAF) operating regions:

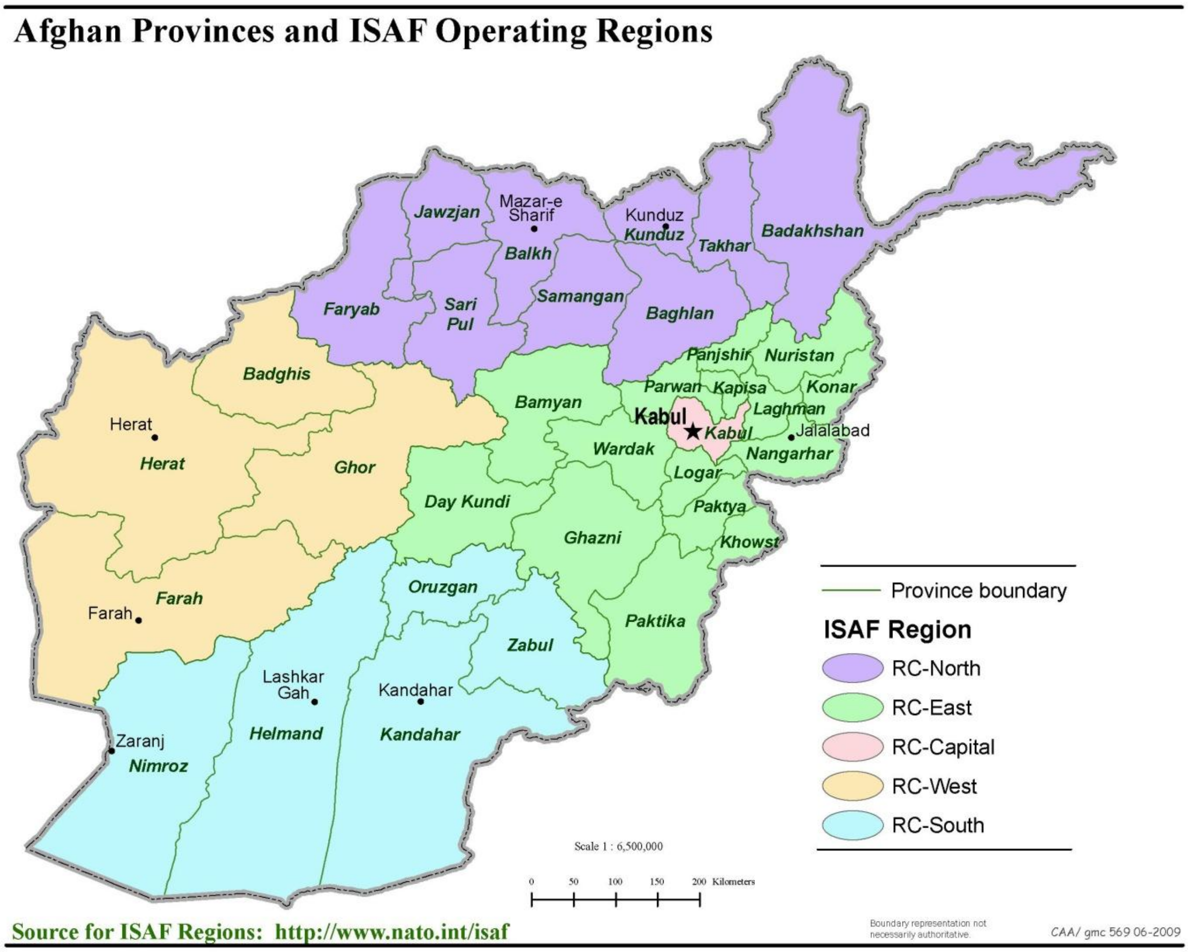

Figure 5: ISAF Operating Regions and Afghan Provinces

As you can see from Figure 5, ISAF military commanders have broken Afghanistan into five distinct regions (RC-WEST, RC-NORTH, RC-EAST, RC-CAPITAL & RC-SOUTH) to illustrate the regions in which both U.S. and NATO combat forces are currently operating for OEF. Additionally, Figure 5 exposes the setting for this MEDEVAC combinatorial optimization problem, specifically the Afghan provinces considered in the experiment.

3.1.2 MEDICAL TREATMENT FACILITY EVACUATION SITES

In order to improve patient survivability in-theatre, combat soldiers who are WIA must be efficiently evacuated by either air or ground medical evacuation assets where highly-trained medics provide in-route medical care before arrival at the closest MTF. Here, the model provides a strategic and tactical solution for the optimal emplacement of aeromedical evacuation assets at medical treatment facility evacuation sites, where all MTFs serve as feasible MEDEVAC helicopter positioning sites.

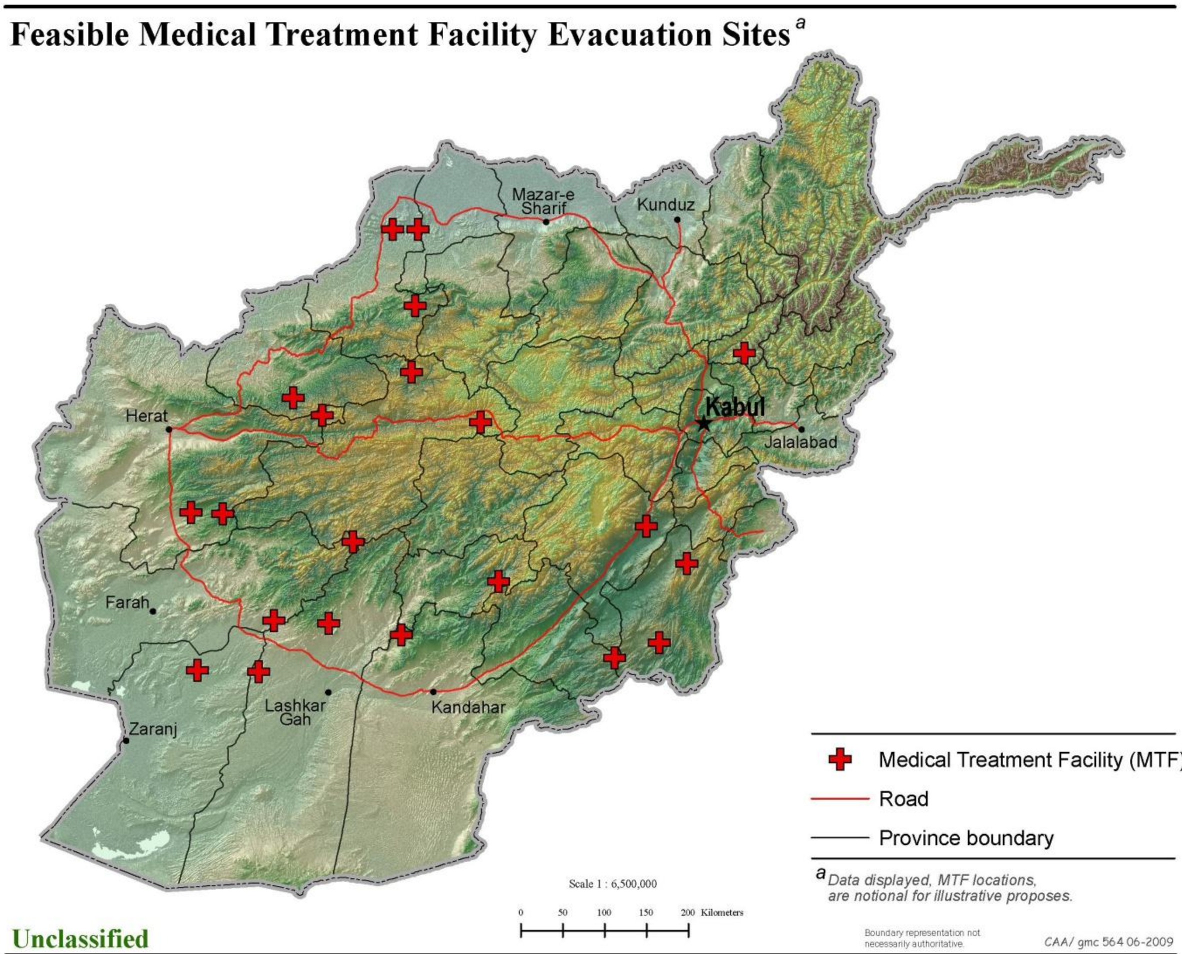

Figure 6: Feasible Medical Treatment Facility Evacuation Sites in Afghanistan

In Figure 6 above, twenty-one MTF sites serve as feasible MEDEVAC helicopter emplacement locations; with the assumption that MEDEVAC assets are co-located at the MTF sites (i.e. MEDEVAC helicopters evacuate WIA casualties to and from the same closest MTF evacuation location). Moreover, these MTF evacuation sites are restricted to pre-determined locations in the OEF theatre due to sustainability requirements such as logistics, maintenance and security. These feasible MTF evacuation sites are plotted by red crosses on a 540x864 nautical-mile grid coordinate system (see Appendix A) to account for MEDEVAC flight times where helicopter velocities are calculated in knots (nautical-miles per hour). Although these twenty-one MTF sites are pre-assigned due to sustainment capabilities, some of them are more susceptible to uncertain enemy insurgent attack than others. Therefore, the model captures the additional importance of optimizing MTF site total vulnerability, ensuring that each evacuation site does not exceed some pre-determined total vulnerability threshold level assigned by the decision-maker. Additionally, the quantity of each MEDEVAC helicopter type in-theatre is fixed due to the long-term nature of steady-state combat operations. Despite this, the decision-maker can utilize this model tactically to re-distribute and re-emplace the aeromedical evacuation assets available on a monthly basis among the feasible MTF evacuation sites to continually optimize the MEDEVAC system based on the three goal program optimization criteria.

3.1.3 U.S. ARMY AREAS OF OPERATION HOTBEDS

Based upon the ISAF regions from Figure 5, the U.S. Army currently has main operating units in both RC-EAST and RC-SOUTH zones. Particularly, the U.S. Army 3rd Brigade 1st Infantry Division and 4th Brigade 101st Airborne Division are currently situated in RC-EAST – Afghan provinces of Nangarhar and Khost, respectively – and the U.S. Army Company D 1st/4th Regiment is located in RC-SOUTH – the Afghan province of Zabul. Moreover, U.S. President Barack Obama recently announced that new U.S. Army Brigade Combat Teams (BCT) will be deploying to Afghanistan in support of OEF. Due to the influx of insurgent and Taliban activity in the southern part of Afghanistan bordering Pakistan, we assume in this experiment that the newly deployed BCTs will be positioned in the Afghan provinces of Farah (RC-WEST) and Kandahar (RC-SOUTH). Figure 7 below illustrates the five locations of these U.S. Army operating units, which will serve as Areas of Operation (AO) ‘Hotbeds’. These AO locations are also plotted on the 540x864 nautical-mile coordinate system, giving the following grid points ({108, 189}, {378, 162}, {270, 162}, {567, 324}, {540, 243}):

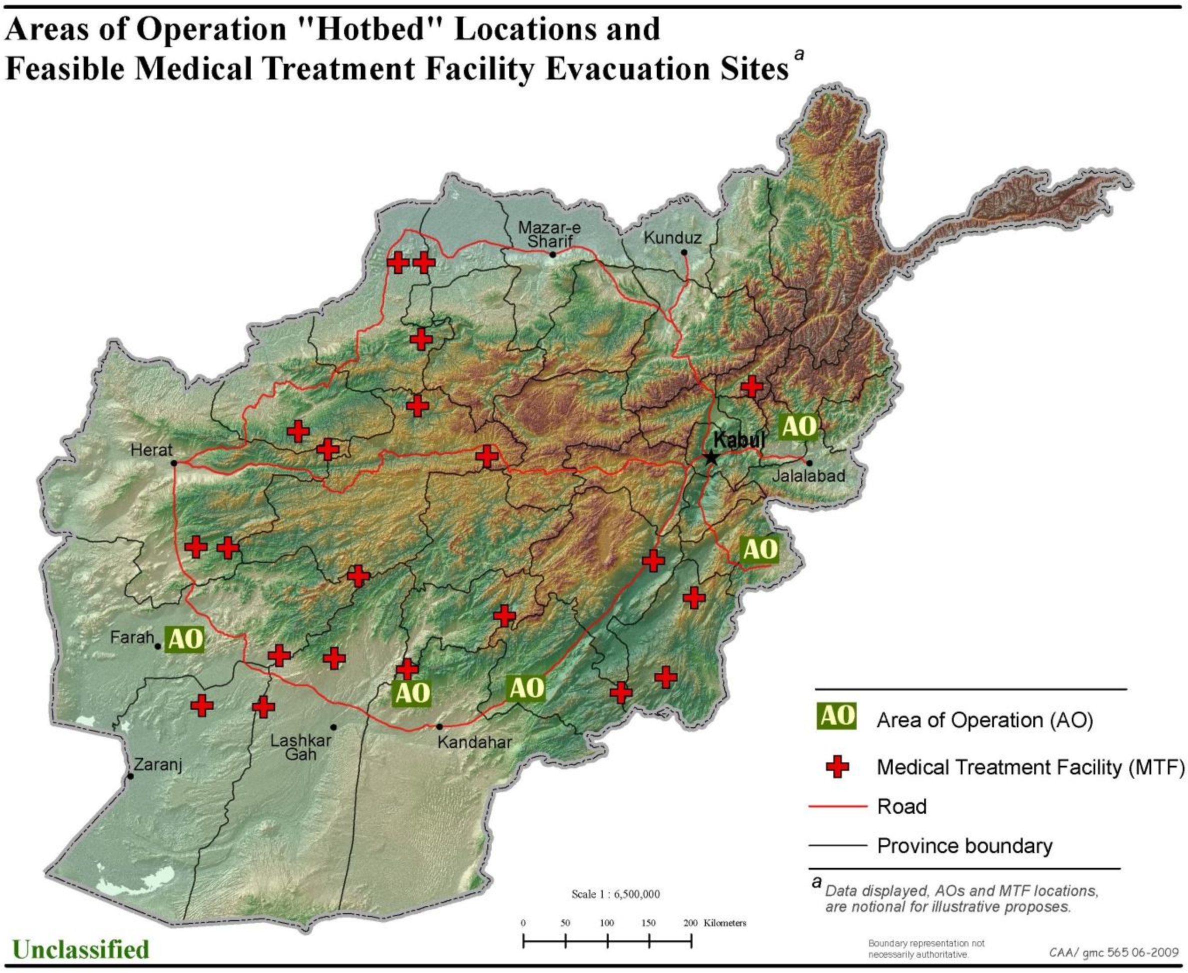

Figure 7: U.S Army Operating Units in Afghanistan

The AO hotbed locations are used later in the experiment to stochastically generate casualty demand sites i and the actual monthly casualty demand (λ_{iw}) within the Afghanistan battlefield, which is the first stage of our two-stage stochastic optimization goal programming model (see Section 3.2.1). The second stage, therefore, is to optimally emplace the helicopters at a subset of the MTF evacuation sites.

3.2 DATA PARAMETER QUANTIFICATION

Inherent in the stochastic optimization goal programming model is the necessity to quantify the geographically variant casualty demand and respective demand locations in Afghanistan, the probability of successfully evacuating WIA casualties within two hours from each demand location, the maximum supportable MEDEVAC demand from helicopters emplaced at MTF evacuation sites, and the vulnerability level of each MTF evacuation site within the different Afghan provinces associated with MEDEVAC routes in and out of each MTF.

3.2.1 CASUALTY GENERATION

Due to uncertainty involved with Taliban and insurgent activity within Afghanistan, future casualty demand numbers and locations must not be determined from purely historical casualty patterns. Instead, U.S. Army medical planners must combine both empirical and stochastic data to best forecast future geographically variant casualty demand. According to OEF casualty statistics posted by the U.S. Department of Defense (DoD) in Figure 8, there have been 2,806 WIA soldiers as of May 4, 2009, since the inception of OEF on October 7, 2001, which averages roughly thirty WIA casualties per month:

OPERATION ENDURING FREEDOM (OEF) U.S. CASUALTY STATUS FATALITIES AS OF: May 4, 2009, 10 a.m. EST					
OEF U.S. Military Casualties	Total Deaths	KIA	Non-Hostile	WIA RTD **	WIA Not RTD *
In and Around Afghanistan***	607	447	160	991	1815
Other Locations****	67	3	64		1
OEF U.S. DoD Civilian Casualties	1	1			
Worldwide Total	**675**	**451**	**224**	**991**	**1,816**

Figure 8: OEF U.S. Casualty Status

For experiment purposes, we assume that all WIA casualties from Figure 8 were air evacuated to a mobile hospital, where roughly one patient was air evacuated per injury location. Therefore, the model stochastically forecasts monthly geographically variant casualty demand with thirty different casualty demand locations, which proves useful for tactical MEDEVAC asset planning each month during steady-state combat operations. Moreover, this experiment assumes that U.S. Army medical planners have selected the five U.S. Army AO hotbeds as prime locations or 'casualty centers' for likely enemy attacks due to the ongoing combat operations and, therefore, casualty demand can be estimated near the Afghan provinces of Nangarhar, Khost, Zabul, Farah, and Kandahar. Furthermore, a frequency distribution then assigns the percent of casualties occurring within each pre-determined AO hotbed location, which is depicted in Table 1 below:

Locations of Casualty Centers		
Grid	Percent of Casualties	
{108, 189}	0.073	**CDF**
{378, 162}	0.180	0.252
{270, 162}	0.180	0.432
{567, 324}	0.284	0.716
{540, 243}	0.284	1.000

Table 1: Pre-determined Locations of Casualty Centers

In Table 1, each AO hotbed grid coordinate is located in one of the Afghan operating regions classified by ISAF. In fact, two of the AOs are co-located in RC-SOUTH and another two AOs are co-located in RC-EAST. Moreover, this casualty frequency distribution using data from Campbell & Shapiro (2008) was determined by dividing the number of Taliban incidents (see Appendix B) in the AO hotbed region by the total number of Taliban incidents that occurred in RC-EAST, RC-WEST and RC-SOUTH. For the two sets of four AOs co-located in the same regions, each casualty center was assigned half of the overall percentage of casualties within its respective region. The distribution in Table 1 provided the baseline for this experiment, even though an actual casualty frequency distribution would be determined more precisely by U.S. Army medical planners. Due to the nature of the ongoing U.S. Army combat operations in the OEF theatre, however, the actual empirical distributions are inaccessible for security purposes.

Despite this, a stochastic mechanism exists for determining casualty demand sites based on these AO hotbed locations and applying uniform randomness to the identified casualty centers. The first step is to assign a random casualty radius around each AO hotbed location. From the 2008 OEF MEDEVAC After Action Review (AAR), the coverage radius for each MEDEVAC aircraft was set at seventy-four nautical-miles for planning purposes. Therefore, this experiment assumes a random uniform casualty generation radius around each AO hotbed location, where mag_{iw} = uniform($-d$, $+d$) and d is one of the DOE scenario factors set at values of fifty or 100 nautical miles. The second step is to generate random uniform angles [ang = uniform(0, 2π)] from the AO hotbed location in the direction in which these casualties are generated. Based on a uniform random number (0, 1) and the casualty cumulative distribution value for the AO casualty center from Table 1, the thirty casualty demand locations i are stochastically determined. Below is an example, but the complete pseudo-code of the method is found in Appendix C:

$$i\,(x_{coord}) = \text{AO site}\,(x_{coord}) + mag_{iw}*\cos(ang)$$
$$i\,(y_{coord}) = \text{AO site}\,(y_{coord}) + mag_{iw}*\sin(ang)$$

Based on this stochastic method for casualty location generation, Figure 9 below illustrates the total number of casualties generated over all eight modeling scenarios. Hence, Figure 9 contains a total of 240 casualty demand locations represented by blue triangles, which clearly surround the five AO hotbed locations and are denser in the RC-EAST region:

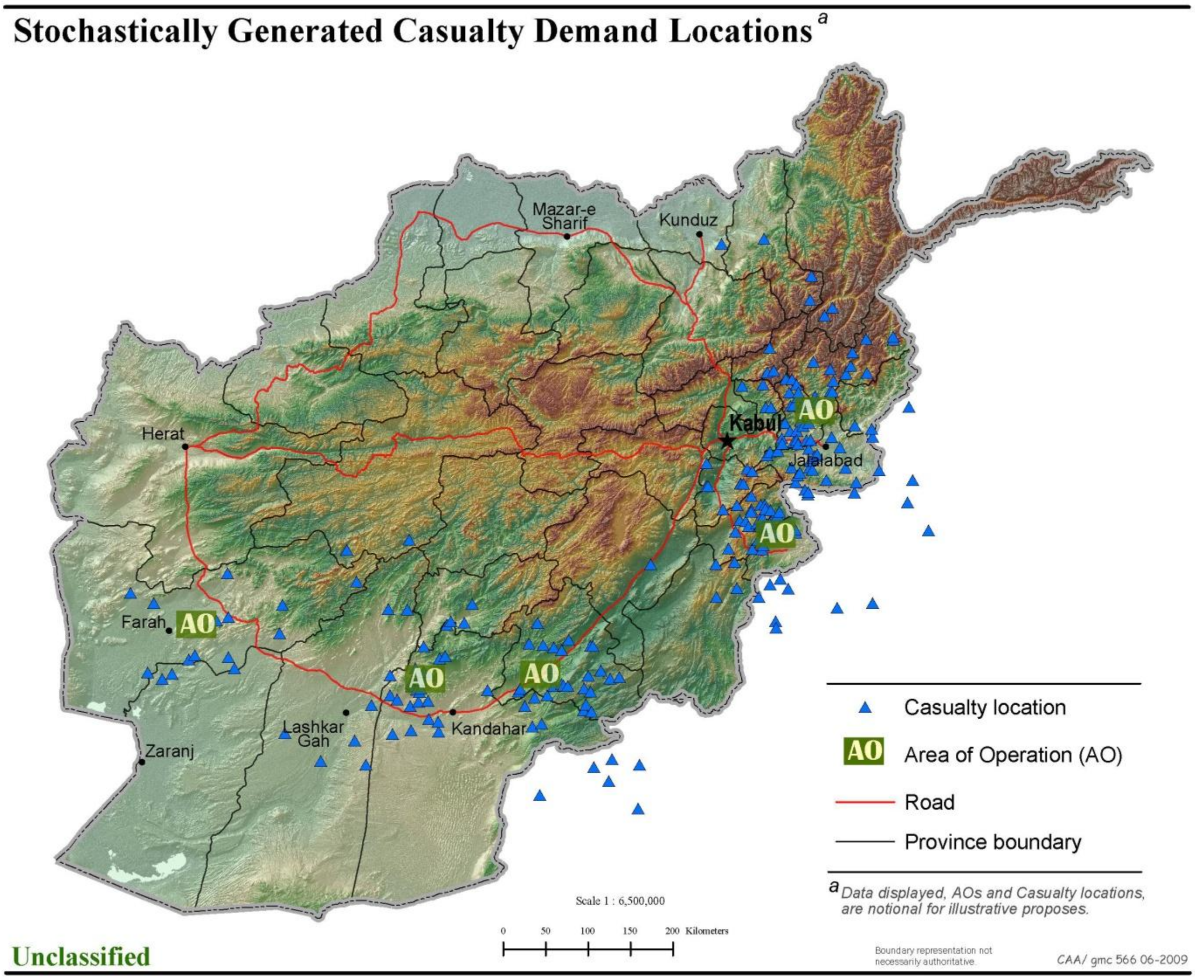

Figure 9: Stochastically Generated Casualty Demand Locations

In addition to stochastic generation of the casualty demand locations, another stochastic element engenders the actual monthly casualty demand originating at each of these locations. Based on Operation Iraqi Freedom MEDEVAC flight logs from the Army Medical Evacuation Proponency Directorate and then adjusted to the OEF casualty situation with thirty WIA soldiers per month, Table 2 provides an approximate probability mass function for determining the number of casualties at a given casualty demand location:

Casualties at Same Location		
Note: Based on 31 WIA/month		
# Patients	P(X=x)	**CDF**
1	0.874	
2	0.086	0.96
3	0.03	0.99
4	0.01	1

Table 2: Number of Casualties at the Same Casualty Demand Location

Next, we model uncertainty regarding enemy capability in the AO hotbed area by applying a lethality factor to the number of casualties generated at each location. Based on 2008 data from Campbell & Shapiro (2008) for Taliban incidents (see Appendix B), maximum and minimum lethality factors were determined by the following equation: 1+ (Number of Taliban incidents in the Afghan province divided by the total number of Taliban incidents in all Afghan provinces), giving a minimum value of 1.00 and a maximum value of 1.154. This lethality factor is applied as a uniform random distribution from the minimum to the maximum value [$leth_{iw}$ = uniform(1.0, 1.154)]. The application of this lethality factor serves to evaluate the lethal sensitivity of the casualty location and the uncertain enemy capabilities. To assign distributions for actual monthly demand at each casualty location (λ_{iw}), we use a uniform random number (0, 1) and the probability mass function from Table 2 for casualties at the same location and apply a lethality factor to the casualties generated at each location. For instance, for every casualty location *i* and scenario w, λ_{iw}= round(# Patients Evacuated at Same Location * $leth_{iw}$) and cas_d_w = sum over all λ_{iw} for each scenario w. Also, to assign the proportion of monthly demand originating in each casualty demand location such that the summation of a_{iw} for all i equals 1 for each scenario w, we assign $a_{iw} = \lambda_{iw} / cas\_d_w$. Please refer to Appendix D for the complete pseudo-code associated with this method for casualty demand generation and Appendix E for a table depicting the actual stochastically determined λ_{iw} values. For further information regarding stochastic casualty generation, please refer to Fulton et al (2009). Now that casualty demand locations and actual demand numbers have been generated, this completes the first-stage of the stochastic goal programming model.

3.2.2 MEDEVAC TIME MONTE CARLO SIMULATION

Another essential aspect of this experiment involves quantification of the probability (P_{ijkw}) of successfully evacuating casualties from each of the thirty newly established casualty demand locations, determined from the first-stage of stochastic optimization model, within two hours; this is calculated for each scenario. Moreover, MEDEVAC helicopters are dispatched from the closest MTF evacuation site where aircraft are positioned and available to retrieve the WIA soldiers and transports them to the closest MTF. In general terms, this data parameter measures the probability of success for each Y_{ijk} 'arcbird' (where the total number of arcbirds represent the product of the thirty casualty demand locations, the twenty-one potential MTF evacuation sites, and the three aircraft models for emplacement). In order to quantify this data parameter for the second-stage of the stochastic goal program, the model conducts a Monte Carlo simulation of 100 trials per arcbird (ensuring minimal computer memory usage and computational running time), where each trial sampling calculates the total MEDEVAC time per trial and scenario ($trial_{ijkwt}$). This data parameter equals the sum of six different MEDEVAC times:

1. <u>The time in each trial from injury at the casualty demand location to notification of a supporting MEDEVAC helicopter in each scenario</u> ($time\_inj_{ijkwt}$). Based on CAA's analysts who queried in-theatre MEDEVAC pilots, this variable is stochastically calculated using their subject matter expertise via a triangular distribution in the simulation with a minimum of five minutes, a maximum of fifteen minutes, and a most likely value of ten minutes (the model computes in hours rather than minutes).

2. <u>The time in each trial from notification to MEDEVAC helicopter wheels up in each scenario</u> ($time\_wup_{ijkwt}$). Based on the 2008 MEDEVAC AAR, in-theatre subject-matter experts estimated a mean time of twenty minutes. From personal MEDEVAC experience, a standard deviation of five minutes deems appropriate. Therefore, this variable is computed using a normal distribution using the estimated mean and estimated standard deviation (the model computes in hours rather than minutes).

3. <u>The flight time in each trial to pickup casualties with a helicopter dispatched from the closest MTF evacuation site in each scenario</u> ($time\_pup_{ijkwt}$). This variable was stochastically calculated from dividing the Euclidean distance between the casualty demand location and the closest MTF evacuation sites ($dist\_pu_{ijkw}$) by a random uniform distribution of MEDEVAC helicopter speeds from 120 to 193 nautical-miles per hour (vel_{ijkwt}). Note that this range of helicopter speeds was based on the assumption that aircraft type K1 is a HH60 Pavehawk, aircraft type K2 is a UH60A-L Blackhawk, and aircraft type K3 is a UH60Q MEDEVAC with normal operating speeds between 120 of 193 knots. Additionally, this MEDEVAC time can be replaced by the value computed from our three-dimensional shortest helicopter path algorithm (discussed in Section 2.3).

4. <u>The patient load time in each trial at the casualty pickup location in each scenario</u> ($time\_ld_{ijkwt}$). Similar to the time in each trial from injury to notification of the supporting MEDEVAC helicopter in each scenario, in-theatre MEDEVAC pilots provided stochastic data to model this variable in the simulation using a triangular distribution with a minimum of five minutes, a maximum of fifteen minutes, and a most likely value of ten minutes (the model computes in hours rather than minutes).

5. <u>The flight time in each trial from the casualty location to drop-off patients at the closest MTF evacuation site in each scenario</u> ($time\_drop_{ijkwt}$). Similar to the flight time in each trial to pickup casualties with a helicopter dispatched from the closest MTF evacuation site in each scenario, this variable was stochastically calculated by

the same means; divide the Euclidean distance between the casualty demand location and the closest MTF evacuation site ($dist\_pu_{ijkw}$) by a random uniform distribution of MEDEVAC helicopter speeds (vel_{ijkwt}). Note that in this experiment MEDEVAC helicopters only conduct evacuation missions to and from the same MTF evacuation site, which permits use of the same previously-determined distance calculation. Again, this MEDEVAC time can be replaced by the value computed from our three-dimensional shortest helicopter path algorithm (discussed in Section 2.3).

6. <u>The patient off-load time at the MTF evacuation site in each trial and each scenario</u> ($time\_offld_{ijkwt}$). Based on the 2008 MEDEVAC AAR, in-theatre subject-matter experts assumed a mean off-load time of five minutes. From personal MEDEVAC experience, a standard deviation of two minutes deems appropriate. Therefore, this variable is computed using a normal distribution using the estimated mean and estimated standard deviation (the model computes in hours rather than minutes).

Again, each trial of the Monte Carlo simulation sums these six essential MEDEVAC times and keeps a count of the number per Y_{ijk} arcbird that meets the two-hour time threshold. From this, the probability of successfully evacuating patients within two hours for all *i, j* and *k* combinations (P_{ijkw}) is calculated by taking the number of trials meeting the threshold divided by the total number of simulation trials; this is executed for each scenario. For the Monte Carlo simulation results, please refer to Appendix F for the maximum probability of success and Appendix G for the average probability of success (where the P_{ijkw} equaling 0 are excluded) for each of the casualty demand locations.

3.2.3 MAXIMUM SUPPORTABLE MEDEVAC DEMAND

The second-stage of the stochastic optimization goal programming model requires the actual quantity of each helicopter model available in-theatre for emplacement at MTF evacuation sites (c_k). Table 3 below depicts the helicopter types and quantities available to support OEF MEDEVAC operations, which are used in this experiment:

Type/Number of Aircraft Available in OEF	
<u>Helicopter Model</u>	<u># Available</u>
K1: HH60 Pavehawk	2
K2: UH60A-L Blackhawk	3
K3: UH60Q MEDEVAC	12

Table 3: Type/Number of Aircraft Available in OEF

Another data parameter essential for the second-stage of the stochastic optimization goal programming model concerns the maximum supportable MEDEVAC demand from each type and quantity of MEDEVAC helicopters emplaced at the potential MTF evacuation sites (r_{jksw}). Before diving into the calculation of this variable, the experiment makes a few assumptions about the number of litters available in each aircraft type (lit_k), the probability that at least one aircraft is available at the closest MTF evacuation site (p_comp), the operational fleet readiness of each aircraft type (o_k), and the actual number of each aircraft type that the model decides to emplace at the MTF evacuation sites (s). Table 4 below depicts the number of litters available in each aircraft type (K1, K2 & K3) within the OEF theatre.

Number of Patient Litters Available	
Helicopter Model	# of Litters Available
K1: HH60 Pavehawk	4 litters
K2: UH60A-L Blackhawk	4 litters
K3: UH60Q MEDEVAC	6 litters

Table 4: Number of Patient Litters Available for each Helicopter type

Additionally, this experiment assumes the probability of at least one available aircraft equals a pre-determined probability of 95%, which we later examine in the sensitivity analysis, and the operational fleet readiness for all aircraft types equals 67.7%. From these data parameter values, the model computes the maximum number of casualties that can be supported via aeromedical evacuation by taking the product of the number of patient litters available depending on aircraft type, the probability that at least one aircraft is available at the MTF evacuation site, the operational fleet readiness level, and the actual number of aircraft models positioned {2, 3 or 4}, for every combination of MTF evacuation sites, helicopter types, number of aircraft emplaced, and model scenarios.

The next section discusses the quantification of MTF site vulnerability, capturing the third optimization goal necessary for the second-stage of this stochastic goal programming model.

3.2.4 MTF SITE VULNERABILITY

As previously mentioned, the third criterion of the multi-criteria stochastic optimization model presented here is to minimize the value of the maximal MTF evacuation site total vulnerability. As a proxy, we assume in this model that the greater the total number of MEDEVAC helicopter dispatches from each MTF evacuation site, then the greater is its respective total vulnerability to enemy attack. Therefore, vulnerability calculations are subject to the amount of enemy activity (i.e. Taliban incidents) within each Afghan province affecting the MEDEVAC route in and out of each MTF evacuation site.

The first step was to develop an enemy capability lethality factor for each potential MTF evacuation site (en_attack_j), which is based on the 2008 data for Taliban and other enemy incidents (see Appendix B).

Degree of Enemy Capability		
Note: Taliban Incidents in Province of a MTF		
Province	**MTF**	**Lethality Factor**
NIMRUZ	E1	1.014
HELMAND	E2	1.090
FARAH	E3	1.025
HELMAND	E4	1.000
KANDAHAR	E5	1.154
HERAT	E6	1.017
HERAT	E7	1.017
BADGHIS	E8	1.012
BADGHIS	E9	1.012
FARAH	E10	1.025
URUZGAN	E11	1.025
ZABUL	E12	1.044
PAKTYA	E13	1.047
PAKTYA	E14	1.047
PANJSHER	E15	1.000
GHAZNI	E16	1.062
GHOR	E17	1.005
GHOR	E18	1.005
FARYAB	E19	1.009
JAWZJAN	E20	1.004
FARYAB	E21	1.009

Table 5: Enemy Capability Lethality Factors

From this data, we determined an enemy capability lethality factor for each Afghan province by using the following equation: 1+ (Number of Taliban incidents in the Afghan province divided by the total number of Taliban incidents in Afghanistan). Each MTF evacuation site is located in an Afghan province (where some share the same province) where MEDEVAC assets are dispatched from the MTF evacuation site to conduct missions. Table 5 (left) shows the lethality factor assigned to each MTF evacuation site, which is equivalent to the enemy capability lethality factor for its respective Afghan province in which it is located and where its operations are conducted. The second step involved the computation of the actual vulnerability value associated with each MEDEVAC route in and out of each MTF evacuation site (v_{jw}). This data was stochastically-determined for each potential MTF helicopter emplacement site from the product of the enemy capability lethality factor per MTF evacuation site and a random uniform probability (0, 1) accounting for the uncertainty of enemy attack within that Afghan province; this was repeated for all modeling scenarios. Additionally, U.S. Army medical planners must determine their desired total vulnerability threshold level for each potential MTF helicopter emplacement site (vc_{jw}), which is used for optimization purposes required in the model. Our solution methodology utilizes this total vulnerability threshold level as one of the scenario DOE factors, which is subject to the desired input of the decision-maker.

This completes the data parameter quantification and assumptions associated with the stochastic optimization goal programming model presented here.

3.3 MODEL IMPLEMENTATION AND SOLUTIONS

Now that the theoretical methods have been established and the data parameters are quantified, our robust, scenario-based, stochastic optimization goal programming model is ready for implementation.

3.3.1 MODEL IMPLEMENTATION FRAMEWORK

The General Algebraic Modeling System (GAMS), Microsoft Excel© and Microsoft Visual Basic© platforms provided the model implementation framework for our robust, multi-criteria decision analysis methodology, particularly for the stochastic casualty generation, Monte Carlo simulation, optimization model solver, statistics generation and reports, and multi-use decision analysis tool. GAMS is an appropriate framework to use when solving problems with multi-dimensional variables, constraints and data parameters. Additionally, the various stochastic calculations utilized the built-in GAMS seed assignment and random number generator, probability functions, and other programming controls necessary for our solution methodology. Lastly, GAMS leveraged the CPLEX mixed integer programming solver to provide the model solutions with a given set of DOE scenarios (see Appendix H for the GAMS programming code).

3.3.2 SCENARIO SIMULATION EXECUTION

Based on the given set of DOE scenarios, our stochastic optimization goal programming model emplaces the minimum number of helicopters at each MTF evacuation site necessary to maximize the aggregate coverage of the theatre-wide MEDEVAC casualty demand and the probability of meeting that casualty demand, while minimizing the value of the maximal MTF evacuation site total vulnerability to enemy attack. Our solution methodology uses a 2^3 factor design for the generation of eight different scenarios to better equip U.S. Army medical planners with a decision analysis tool useful for future strategic and tactical MEDEVAC asset planning. Moreover, the decision-maker has full access to adjust each of these scenario DOE factors, as discussed in Section 2.2.7, to best use the model as an instrument for decision analysis. Also, each design scenario has a respective probability of occurrence assigned by the decision-maker, which is part of the optimization model objective function. Table 6 (below) summarizes each of the design scenarios executed in this model simulation.

DOE Scenario Factors						
	occur	**P1**	**P2**	**P3**	**casrad**	**vuln**
1	0.125	500	0.2	0.5	50.0	1.010
2	0.125	500	0.2	0.5	50.0	1.005
3	0.150	500	0.2	0.5	100.0	1.010
4	0.100	500	0.2	0.5	100.0	1.005
5	0.125	600	0.6	0.3	50.0	1.010
6	0.125	600	0.6	0.3	50.0	1.005
7	0.100	600	0.6	0.3	100.0	1.010
8	0.150	600	0.6	0.3	100.0	1.005

Table 6: Scenario Design Factors for Simulation

In this simulation experiment, we made smart estimates of the goal priority weights (P1, P2 & P3), casualty radii (casrad), total vulnerability threshold levels (vuln), and probabilities of occurrence (occur) for each scenario. Also, after running the model consecutively we noticed that the value of the goal priority weights clearly had a large influence on the resulting optimal solution. Therefore, we expanded the model to generate a pre-decided number of solutions (ten in our experimental study) necessary to conduct a sensitivity analysis on the goal priority weights as well as the helicopter reliability percentage (see Section 3.4.3).

3.3.3 MODEL FORMULATION SOLUTIONS

For the following solutions representing the two different model formulations, the simulation and optimization was solved on a Dell Precision M60 laptop with a Pentium M 1.7 GHZ processor and 2GB of RAM. Both model formulation solutions below were found using the CPLEX MIP solver embedded within the GAMS platform. The first model solution contained nine blocks of equations, seven blocks of variables, 39,919 non-zero elements, 806 single equations, and 2,601 single variables. The second model solution contained ten blocks of equations, eight blocks of variables, 39,928 non-zero elements, 814 single equations, and 2,602 single variables. In both model formulations, there were a total of 2,079 binary variables representing the 1,890 Y_{ijk} arcbirds and the 189 X_{jks} MEDEVAC helicopter emplacement location options (the twenty-one potential MEDEVAC emplacement sites times three aircraft model types times {2, 3, 4} helicopters positioned at each MTF evacuation site). The CPLEX MIP solver found an optimal solution for both model formulations in less than one minute each, which proves useful for tactical MEDEVAC asset planning. The solution for the second model formulation required nearly ten times the number of iterations and nearly 1000 times the number of branch-and-bound nodes. Both solutions, however, required a similar number of valid cut inequalities. Table 7 depicts the GAMS solution for the first model formulation and Table 8 shows the GAMS solution for the second model formulation:

GAMS Solution #1	
GUB cover cuts:	44
Clique cuts:	2
Cover cuts:	36
Implied bound cuts:	80
Flow cuts:	8
Gomory Fractional cuts:	9
Iterations:	1,236
Branch-and-Bound nodes:	0
Generation Time (seconds):	0.090
Execution Time (seconds):	**36.392**
Memory Used (MB):	519

Table 7: Model Formulation #1 GAMS Solution

GAMS Solution #2	
GUB cover cuts:	39
Cover cuts:	29
Implied bound cuts:	41
Flow cuts:	3
Gomory Fractional cuts:	8
Iterations:	10,355
Branch-and-Bound nodes:	942
Generation Time (seconds):	0.151
Execution Time (seconds):	**33.078**
Memory Used (MB):	519

Table 8: Model Formulation #2 GAMS Solution

3.4 RESULTS AND ANALYSIS

This section presents the results and analysis of our robust, multi-criteria decision analysis methodology. Specifically, this weighted goal programming model optimizes over a given set of expected DOE scenarios to first stochastically generate the future casualty demand locations and actual monthly demand and then identify the optimal subset of MTF evacuation sites for the supporting MEDEVAC helicopters, and the type and number of aircraft to emplace at each MTF site. In addition to displaying the graphical results, this section reports the descriptive statistics and sensitivity analyses from both model formulation solutions.

3.4.1 GRAPHICAL RESULTS

The graphical results of both optimization model formulations have nearly equal solutions for the first-stage decision of where to generate casualties and the second-stage decision of how many, which type and where to optimally emplace MEDEVAC helicopters at a subset of the MTF evacuation sites. The analysis of this experiment clearly shows that both model formulations output identical results, except for the fact that the emplacement of aircraft types K1 and K3 are swapped at MTF sites E10 and E16 (see Figure 10 and Figure 11). Also, MEDEVAC dispatch distributions differ slightly in both model solutions. Otherwise, both model solutions have equivalent types and quantities of MEDEVAC helicopters optimally positioned to successfully evacuate casualties within the two-hour threshold.

For both model formulation solutions, Table 9 and Table 10 below depict the optimal subsets of MTF evacuation sites for helicopter emplacement, the type and quantity of aircraft to position at the chosen MTF evacuation sites, and the percent of total casualties evacuated by MEDEVAC helicopters dispatched from each MTF evacuation sites among the subset:

Model Formulation #1 MTF and Helicopter Emplacements						Percent Evacuated
MTF	X	Y	K1	K2	K3	
E3	173	186		2		15.3%
E4	224	173			2	12.9%
E10	243	221	2			11.8%
E11	335	194			2	11.8%
E12	432	162			2	11.8%
E14	486	208			2	10.6%
E15	537	354			2	14.1%
E16	440	221			2	11.8%

Table 9: Optimal MEDEVAC Emplacement for Model Formulation #1 Solution

Model Formulation #2 MTF and Helicopter Emplacements						Percent Evacuated
MTF	X	Y	K1	K2	K3	
E3	173	186		2		16.7%
E4	224	173			2	10.3%
E10	243	221			2	14.1%
E11	335	194			2	12.8%
E12	432	162			2	10.3%
E14	486	208			2	12.8%
E15	537	354			2	12.8%
E16	440	221	2			10.3%

Table 10: Optimal MEDEVAC Emplacement for Model Formulation #2 Solution

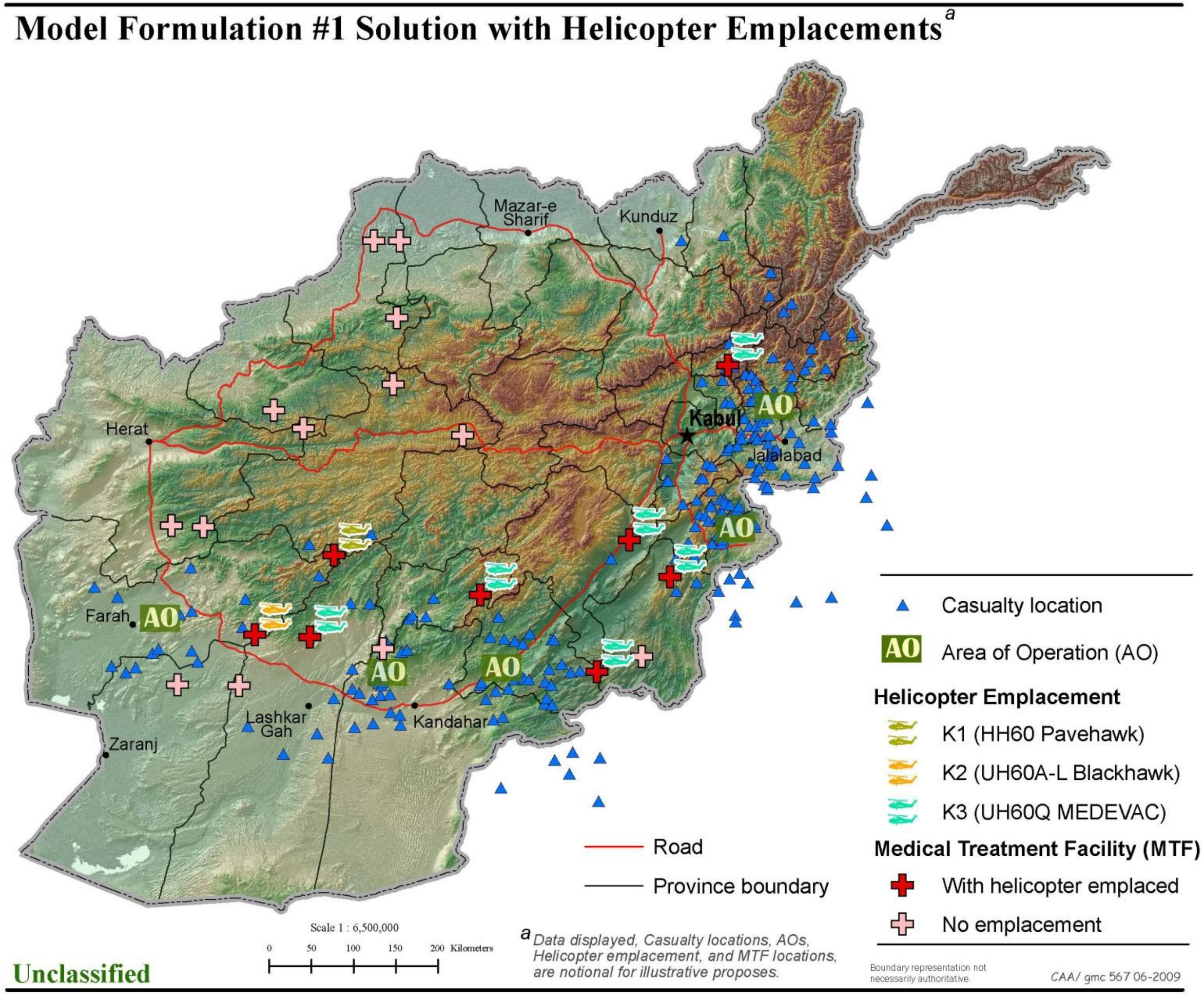

Figure 10: Model Formulation #1 Solution with Helicopter Emplacements

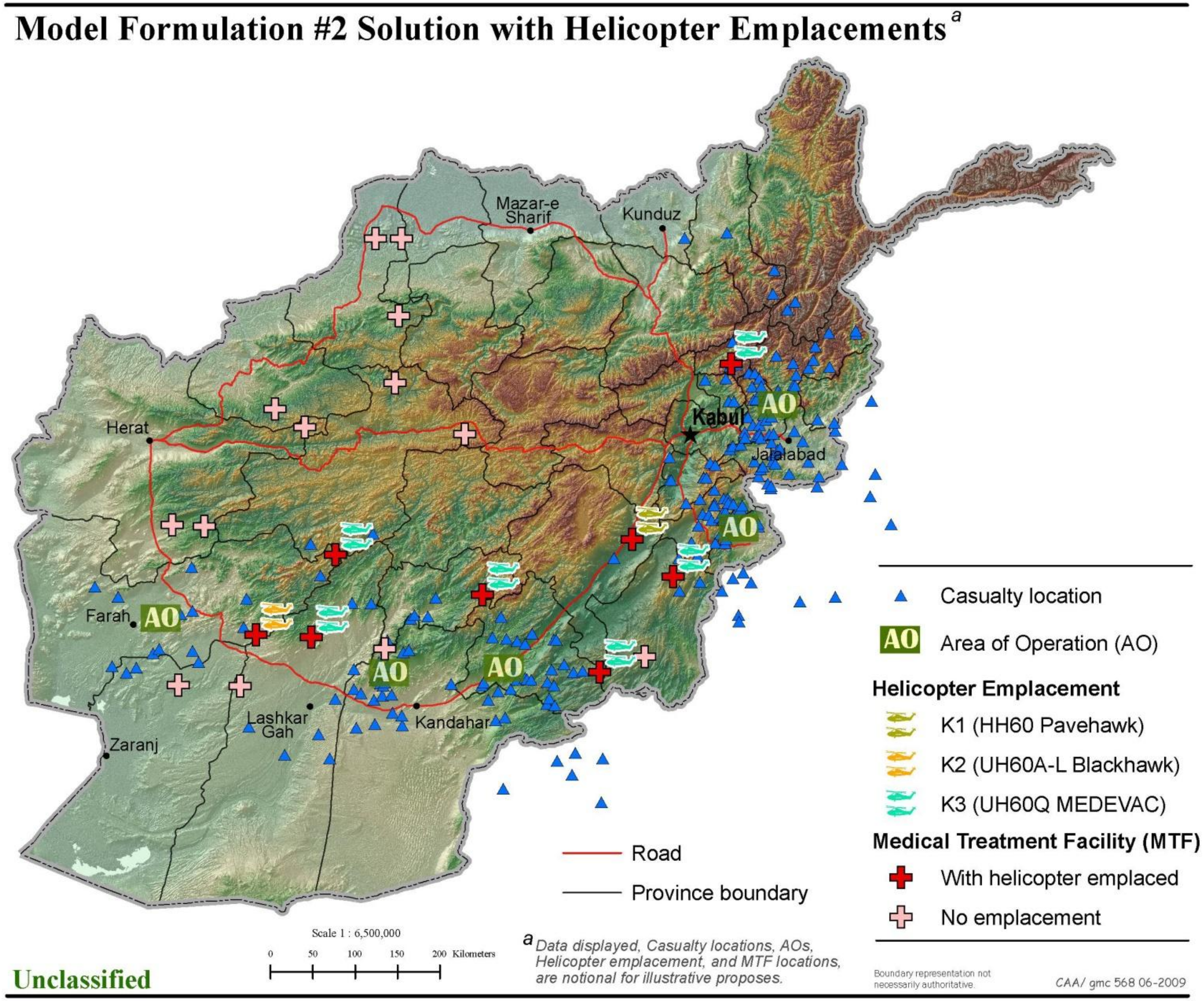

Figure 11: Model Formulation #2 Solution with Helicopter Emplacements

3.4.2 DESCRIPTIVE STATISTICS

Descriptive statistics for the modeling scenarios are generated within our model implementation framework to capture the casualty generation, helicopter positioning, distance/speed/time, and scenario sampling statistics. Table 11 below pertains to these statistics for the first model:

Descriptive Statistics Formulation #1		Design of Experiment Factor Scenarios								
		1	2	3	4	5	6	7	8	Average
Total Number of Casualties Generated		35	32	35	38	38	36	37	33	36
Total Number of Casualties Evacuated from Casualty sites to_from MEDEVAC Helicopters Emplaced at a MTF	**E3**	2	1	1	2	2	3	1	1	1
	E4	1	1	1	1	2	1	3	1	1
	E10	1	1	1	1	1	1	3	1	1
	E11	1	1	3	1	1	1	1	1	2
	E12	1	1	1	2	2	1	1	1	1
	E14	1	1	1	1	2	1	1	1	1
	E15	1	2	4	1	1	1	1	1	2
	E16	1	2	1	1	1	1	1	2	1
Number of WIA Evacuated		9	10	13	10	12	10	12	9	11
Percent of Total Casualties Evacuated		26%	31%	37%	26%	32%	28%	32%	27%	30%
Total distance traveled per month (NM) to_from MEDEVAC Helicopters Emplaced at a MTF to Evacuate WIAs	**E3**	441.0	720.2	200.1	411.5	418.4	59.8	1001.1	148.7	425.1
	E4	702.7	121.9	649.8	766.7	42.6	327.3	50.9	66.0	341.0
	E10	589.5	598.4	143.1	36.7	685.4	201.2	37.4	210.0	312.7
	E11	164.7	565.1	119.1	157.9	152.1	171.1	174.3	85.9	198.8
	E12	149.8	302.4	704.6	54.9	137.4	352.8	126.8	420.4	281.1
	E14	446.2	294.9	135.1	91.4	70.4	126.4	162.0	255.7	197.8
	E15	456.7	39.1	29.8	44.3	140.4	576.9	111.2	36.7	179.4
	E16	231.0	58.8	362.0	332.8	308.5	126.4	437.0	85.4	242.7
Mean MEDEVAC Distance for all WIAs		452.8	349.8	333.9	295.3	328.0	257.7	284.7	174.3	309.6
Mean MEDEVAC Velocity for all WIAs		157.3	157.3	155.9	155.5	156.3	156.7	156.3	156.7	156.5
Mean MEDEVAC Time for all WIAs		2.88	2.22	2.14	1.90	2.10	1.64	1.82	1.11	2.0
E(X^2) for Simulation Average Total MEDEVAC Time		16.2	11.3	10.6	11.0	11.0	6.8	10.3	4.1	
(E(X))^2 for Mean MEDEVAC Time for all WIAs		8.3	4.9	4.6	3.6	4.4	2.7	3.3	1.2	
Standard Deviation of MEDEVAC Time		1.00	0.89	0.87	0.96	0.91	0.71	0.94	0.60	
Final Standard Error		8.7%								

Table 11: Descriptive Statistics for Model Formulation #1 Solution

Additionally, Table 12 below depicts the descriptive statistics associated with the second model formulation solution:

Descriptive Statistics Formulation #2		Design of Experiment Factor Scenarios								
		1	2	3	4	5	6	7	8	Average
Total Number of Casualties Generated		35	32	35	38	38	36	37	33	36
Total Number of Casualties Evacuated from Casualty sites to_from MEDEVAC Helicopters Emplaced at a MTF	E3	2	1	1	2	2	3	1	1	1
	E4	1	1	1	1	1	1	1	1	1
	E10	1	1	1	1	2	1	3	1	1
	E11	1	1	1	1	1	3	1	1	1
	E12	1	1	1	1	1	1	1	1	1
	E14	1	2	1	1	1	1	1	2	1
	E15	1	1	1	1	2	1	1	2	1
	E16	1	1	1	1	1	1	1	1	1
Number of WIA Evacuated		9	9	8	9	11	12	10	10	10
Percent of Total Casualties Evacuated		25.7%	28.1%	22.9%	23.7%	28.9%	33.3%	27.0%	30.3%	27.5%
Total distance traveled per month (NM) to_from MEDEVAC Helicopters Emplaced at a MTF to Evacuate WIAs	E3	441.0	720.2	200.1	411.5	418.4	59.8	1001.1	148.7	425.1
	E4	303.8	744.8	622.7	111.2	51.2	219.9	588.7	151.4	349.2
	E10	636.5	164.5	593.2	697.0	64.2	296.4	82.8	139.7	334.3
	E11	567.0	417.3	577.4	620.1	89.4	143.9	538.4	45.4	374.9
	E12	314.2	483.7	112.1	611.2	263.1	591.6	532.0	170.3	384.8
	E14	158.1	75.5	431.3	278.9	286.0	31.1	386.5	43.6	211.4
	E15	233.8	550.8	83.7	15.9	334.8	528.2	662.5	52.9	307.8
	E16	624.3	343.9	170.8	202.5	202.2	108.2	324.6	99.9	259.5
Mean MEDEVAC Distance for all WIAs		465.0	447.0	348.9	420.0	315.8	298.3	535.3	118.5	368.6
Mean MEDEVAC Velocity for all WIAs		155.9	156.4	157.3	157.0	157.2	156.9	157.1	156.6	156.8
Mean MEDEVAC Time for all WIAs		2.98	2.86	2.22	2.68	2.01	1.90	3.41	0.76	2.35
E(X^2) for Simulation Average Total MEDEVAC Time		16.7	15.2	10.9	15.5	10.7	8.7	19.8	2.4	
(E(X))^2 for Mean MEDEVAC Time for all WIAs		8.9	8.2	4.9	7.2	4.0	3.6	11.6	0.6	
Standard Deviation of MEDEVAC Time		0.99	0.93	0.86	1.02	0.91	0.79	1.01	0.48	
Final Standard Error		11.5%								

Table 12: Descriptive Statistics for Model Formulation #2 Solution

From the descriptive statistics displayed in Table 11 and Table 12, the total number of casualties generated in the first-stage of our stochastic optimization goal programming model was equivalent for both model formulation solutions with an average of thirty-six casualties generated per month, which is based on the probability mass function for the number of casualties evacuated from the same location used in our experiment. This amount slightly exceeds the historical, deterministic data of thirty-one WIA soldiers per month.

Additionally, it is interesting to note the actual number and percentage of casualties evacuated, where only an average of 27.5% and 30% of total casualties were evacuated each month. The reason for these low amounts and percentages of evacuated WIA soldiers directly correlates to the P_{ijkw} values, the probability of successfully evacuating patients from each of the casualty demand locations within two hours. Although Appendix F – depicting the maximum probability of successful casualty evacuation at each casualty location – illustrates that most of the casualty locations have a maximum success rate of 100% for each of the scenarios, Appendix G displays more accurate data concerning the average probabilities of success. Hence, the overall average probability of successfully evacuating casualties within two hours from all casualty demand locations over all scenarios equals 63%. These averages, however, do not account for the combinations of *i*, *j* and *k* with success rates of 0% (if this were the case, then the average percentages would be much lower around 10 to 20%). In fact, most of the combinations of *i*, *j* and *k* have success probabilities of 0% because of the location we set for each AO hotbed, their distance away from the pre-determined feasible MTF evacuation sites, and our stochastic method for generating casualties up to 100 nautical miles away from an AO hotbed location. Regardless of these casualty statistics, nearly all of the WIA soldiers will be evacuated from the casualty demand locations in an actual combat environment despite the two-hour MEDEVAC time threshold.

Also, Table 11 and Table 12 display the mean MEDEVAC distance, velocity and time statistics as well as the sampling statistics for each modeling scenario. These statistics consider all MEDEVAC times to evacuate casualties and not simply times under the two-hour threshold. Therefore, it is interesting to note that the average over all scenarios of mean MEDEVAC times was roughly two hours for both model formulation solutions. Additionally, the final standard error between the Monte Carlo simulation average MEDEVAC time and the mean MEDEVAC time over all scenarios is less than 12% in both model formulation solutions (Note: Euclidean distance is used for these time calculations).

3.4.3 SENSITIVITY ANALYSES

As stated earlier, our model executes a preset number of times to better aid the decision-maker with a range of solutions as well as perform sensitivity analyses on two different model data parameters. Particularly, we analyzed solution sensitivity for both model formulations by measuring the impact on the number of casualties evacuated per month when changing each goal priority weight and the probability that at least one helicopter is available to conduct a MEDEVAC mission. It is evident that the priority weight of Goal #1 has the greatest impact on the optimal solution when compared with the two other goal weights. Figure 12, Figure 13 and Figure 14 below show the goal priority weight sensitivity analyses for the first model formulation, which compares the average priority goal weight with the average number of casualties evacuated over ten runs:

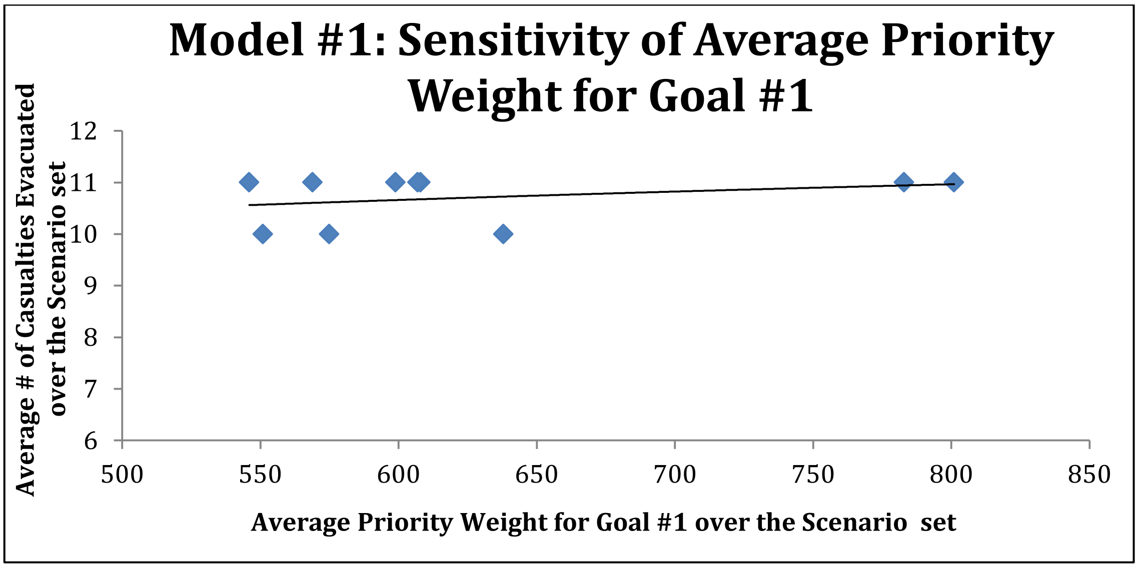

Figure 12: Model #1 Sensitivity of Average Priority Weight for Goal #1

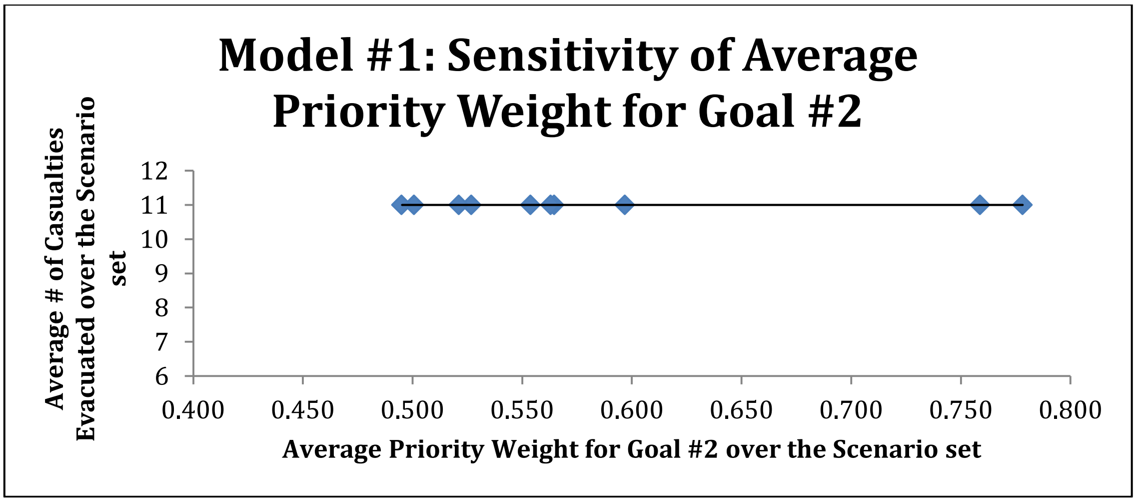

Figure 13: Model #1 Sensitivity of Average Priority Weight for Goal #2

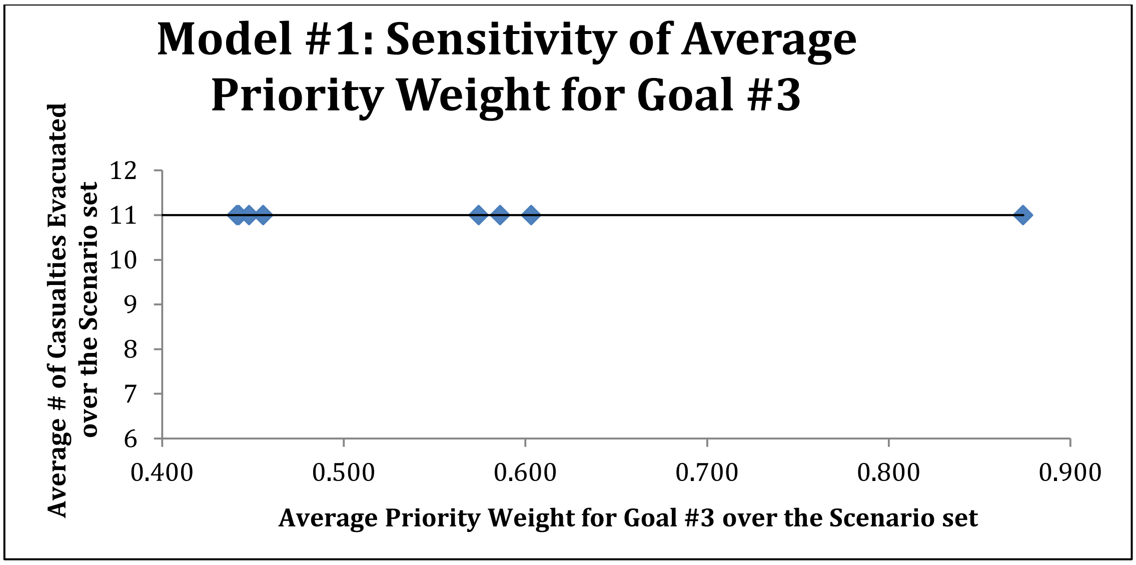

Figure 14: Model #1 Sensitivity of Average Priority Weight for Goal #3

It is clear from Figure 13 and Figure 14 that the average number of casualties evacuated over the scenario set is not sensitive to the second or third goal priority weights, but Figure 12 illustrates an increasing linear relationship between the first goal weight and the number of casualties evacuated. Additionally, we tested the sensitivity of the helicopter availability reliability from 90% to 100% probability that at least one helicopter is available on a MTF evacuation site but found no significant relationship; this is depicted in Figure 15 below:

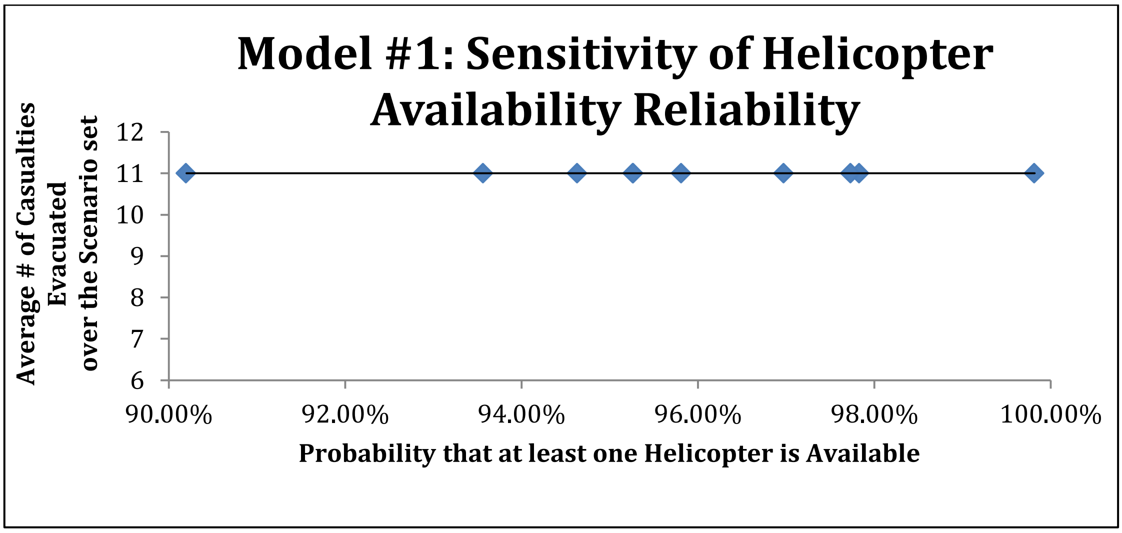

Figure 15: Model #1 Sensitivity of Helicopter Availability Reliability

We conducted an identical sensitivity analysis for the second model formulation solutions, but we found no differences except for the sensitivity of the second goal priority weight. Unlike the first model formulation, Figure 16 below shows a slight linear increasing relationship between the second goal priority weight and the number of casualties evacuated for the second model formulation solution:

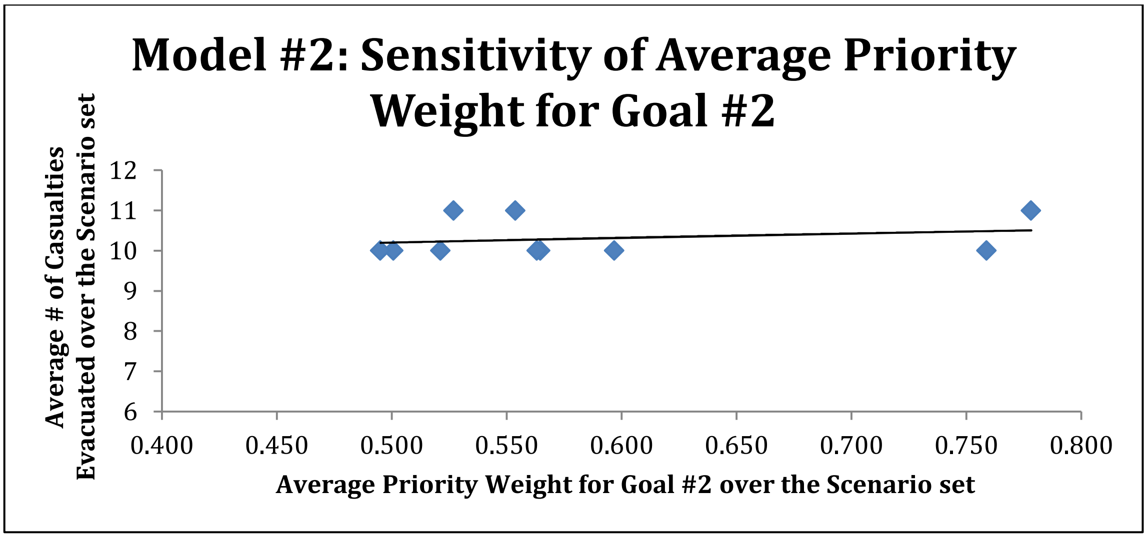

Figure 16: Model #2 Sensitivity of Average Priority Weight for Goal #2

The results and analysis presented here clearly highlight the functionality of our scenario-based, stochastic optimization goal programming model for determining the optimal emplacement (with respect to aircraft type and quantity) of MEDEVAC helicopters at a subset of feasible MTF evacuation sites such that the aggregate expected casualty demand coverage is maximized while the MEDEVAC helicopter spare capacities and maximal MTF site total vulnerability are minimized. Furthermore, the solutions to our experiment concerning the Afghanistan MEDEVAC asset optimization problem are based on notional input data for U.S. Army security purposes as well as numerous assumptions made for quantification of the model data parameters. Last, it is evident from the descriptive statistics and sensitivity analyses that our optimal solutions obtained from both model formulations are influenced by numerous factors as previously discussed.

4 CONCLUSIONS AND RECOMMENDATIONS

4.1 CONCLUSIONS

Although more casualties survive compared to any other war due to the current Health Service Support system, the U.S. Army can still greatly improve its systematic approach to treat and air evacuate casualties from combat zones in order to maintain a healthy force and to conserve combat strength of deployed soldiers. Since the beginning of Operation Enduring Freedom, military commanders have faced a significant combinatorial challenge integrating limited air evacuation assets into a comprehensive system for the entire combat theatre. As a pillar of military medical doctrine, optimizing the emplacement of responsive field-sited medical treatment facilities and aeromedical evacuation assets can increase survivability for those wounded soldiers air evacuated from the battlefield. Furthermore, thorough investigation and development of improved analytical solutions derived from objectives concerning casualty coverage, MEDEVAC helicopter utilization, and vulnerability to enemy attack measures directly supports the military medical mission.

This work described a robust, multi-criteria decision analysis methodology using a scenario-based, stochastic optimization goal programming model for U.S. Army medical planners to use as a strategic and tactical aeromedical evacuation asset planning tool to help sustain and improve the aeromedical evacuation system in Afghanistan. Specifically, this two-stage model first generated casualty demand locations and then optimized over a set of expected scenarios based on these stochastically-determined casualty locations to emplace the minimum number of helicopters at each medical treatment facility necessary to maximize the coverage of the theatre-wide casualty demand and the probability of meeting that demand, while minimizing the maximal medical treatment facility evacuation site total vulnerability.

Although our solution methodology used in the experiment focused on optimizing the U.S. Army's aeromedical evacuation system in Afghanistan, the results clearly demonstrate that our model can be employed as a useful analytical tool for decision-makers seeking to optimize the emplacement of limited resources based on the probability of covering geographically variant demand requirements. Our decision analysis methodology utilizes multi-criteria, scenario planning and stochastic optimization methods to help support tactical MEDEVAC asset planning for steady-state military operations. Endless opportunities exist to utilize our solution methodology within and outside the military medical community.

4.2 LIMITATIONS AND FUTURE WORK

The results of our experiment are limited to the assumptions made and the data used during model development. Therefore, our experiment would improve with 2009 MEDEVAC data from in-theatre subject matter experts, particularly to fine-tune the quantification of numerous model data parameters and the various probability distributions.

As seen from our results and analyses, optimal model solutions are heavily dependent on the DOE scenarios input by the decision-maker, where the priority weight of the first optimization goal has the greatest sensitivity. Additionally, our solution methodology is limited by the probability of successfully evacuating patients from each of the casualty demand locations within two hours. This data parameter greatly affects the number and percent of actual monthly WIA casualty evacuations. Future work is needed to further develop and implement our three-dimensional shortest helicopter path algorithm to compute this essential model data parameter. Our algorithm implementation remains a work-in-progress due to the complexity associated with data collection for the feasibility conditions (as the real data is classified) and the algorithm inputs, yet proves useful as a future modeling add-in for more accurate three-dimensional helicopter flight times during combat operations.

Moreover, this experiment utilizes only a small sample of air ambulance and medical treatment facility attributes. The addition of attributes, however, increases problem complexity and slows the model computation time, which is a significant limitation for tactical MEDEVAC asset optimization. Also, our methodology only considers a monthly planning time horizon as opposed to multi-period analysis because multi-period analysis is not particularly useful for geographically variant resource emplacement in military stability operations. Nonetheless, a multi-period extension to the model would be useful for strategic medical modeling in non-stability combat operations where the operations tempo varies over time and sufficient planning over multiple time periods is necessary.

Further expansion of the model is needed to account for ground casualty evacuation assets and not only MEDEVAC helicopter emplacement. This methodology can also be extended to account for medical treatment facility patient capacities as well as inserting parameters that model future capabilities of evacuation and hospital assets. The model, however, can be easily re-formulated to account for these changes as well as different objective functions and constraints. Future areas of research concern dynamic approaches and techniques for military medical modeling to assist U.S. Army medical planners in both ground and air evacuation asset scheduling and routing decisions.

4.3 ACKNOWLEDGMENTS

This work could not have been done without the thankless professional support and development from Dr. Alexander Grigoriev, my thesis advisor at Universiteit Maastricht, Mr. Jack Zeto, LTC Wade Yamada and Ms. Gale Collins at the Center for Army Analysis, LTC(P) Larry Fulton at the Center for AMEDD Strategic Studies, the Medical Evacuation Proponency Directorate, and the Department of Systems Engineering at West Point.

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5 APPENDICES

5.1 APPENDIX A: MEDICAL TREATMENT FACILITY LOCATIONS

Province	MTF	X	Y
NIMRUZ	E1	108	157
HELMAND	E2	162	157
FARAH	E3	173	186
HELMAND	E4	224	173
KANDAHAR	E5	278	170
HERAT	E6	113	256
HERAT	E7	154	254
BADGHIS	E8	197	327
BADGHIS	E9	216	319
FARAH	E10	243	221
URUZGAN	E11	335	194
ZABUL	E12	432	162
PAKTYA	E13	470	170
PAKTYA	E14	486	208
PANJSHER	E15	537	354
GHAZNI	E16	440	221
GHOR	E17	335	302
GHOR	E18	286	337
FARYAB	E19	286	378
JAWZJAN	E20	297	424
FARYAB	E21	273	427

These twenty-one medical treatment facility locations plotted on a nautical-mile grid coordinate system represent the feasible helicopter emplacement sites within the experiment.

5.2 APPENDIX B: TALIBAN/INSURGENT ACTIVITY IN AFGHANISTAN

(FIGURE 1.24) COMPARISON OF INCIDENTS CARRIED OUT BY TALIBAN/ANTI-GOVERNMENT ELEMENTS (TB/AGE), WEEKS 1-27 (JANUARY THRU MID-JULY) FOR 2007 AND 2008[26]

REGIOANAL COMMAND/ PROVINCE	2007	2008	% CHANGE
RC CAPITAL			
KABUL	**60**	**81**	**35%**
RC EAST			
PARWAN	14	34	143%
WARDAK	72	133	85%
PANJSHER	0	1	N/A
LOGAR	76	98	29%
KAPISA	26	81	212%
KHOST	240	301	25%
PAKTYA	124	169	36%
GHAZNI	113	221	96%
PAKTIKA	102	151	48%
NANGARHAR	170	193	14%
LAGHMAN	72	107	49%
NURISTAN	40	41	3%
KUNAR	321	331	3%
BAMYAN	1	2	100%
RC EAST TOTAL	**1,371**	**1,863**	**36%**
RC SOUTH			
KANDAHAR	330	552	67%
HELMAND	107	323	202%
NIMROZ	22	49	123%
URUZGAN	41	91	122%
ZABUL	163	158	-3%
DAI KUNDI	10	8	-20%
RC SOUTH TOTAL	**673**	**1,181**	**75%**
RC WEST			
BADGHIS	17	69	306%
HERAT	50	60	20%
GHOR	11	19	73%
FARAH	72	90	25%
RC WEST TOTAL	**150**	**238**	**59%**
RC NORTH			
FARYAB	18	34	89%
JAWZJAN	5	14	180%
SARI PUL	14	2	-86%
BALKH	31	25	-19%
SAMANGAN	4	3	-25%
KUNDUZ	23	68	196%
BAGHLAN	44	42	-5%
TAKHAR	14	17	21%
BADAKSHAN	10	22	120%
RC NORTH TOTAL	**163**	**227**	**39%**
TOTAL, ALL REGIONS	**2,417**	**3,590**	**49%**

5.3 APPENDIX C: GENERATING CASUALTY LOCATIONS PSEUDO-CODE

```
If (rand1(i, w) <= .073,
        cas(i,'X',w)=ao('X','1') + mag(i,w) * cos(casx(i,w));
        cas(i,'Y',w)=ao('Y','1') + mag(i,w) * sin(casy(i,w));
else if (rand1(i, w) <=.252),
        cas(i,'X',w)=ao('X','2') + mag(i,w) * cos(casx(i,w));
        cas(i,'Y',w)=ao('Y','2') + mag(i,w) * sin(casy(i,w));
else if (rand1(i, w) <= .432),
        cas(i,'X',w)=ao('X','3') + mag(i,w) * cos(casx(i,w));
        cas(i,'Y',w)=ao('Y','3') + mag(i,w) * sin(casy(i,w));
else if (rand1(i, w) <= .716),
        cas(i,'X',w)=ao('X','4') + mag(i,w) * cos(casx(i,w));
        cas(i,'Y',w)=ao('Y','4') + mag(i,w) * sin(casy(i,w));
else
        cas(i,'X',w)=ao('X','5') + mag(i,w) * cos(casx(i,w));
        cas(i,'Y',w)=ao('Y','5') + mag(i,w) * sin(casy(i,w));
);
```

5.4 APPENDIX D: GENERATING CASUALTY DEMAND PSEUDO-CODE

```
loop(i,
        leth(i,w) = uniform(1.0,1.154);
        if(rand2(i,w) <= .874,
                lambda(i,w) = round(1*leth(i,w));
        elseif (rand2(i,w) <= .96),
                lambda(i,w) = round(2*leth(i,w));
        elseif (rand2(i,w) <= .99),
                lambda(i,w) = round(3*leth(i,w));
        else
                lambda(i,w) = round(4*leth(i,w));
        );
        cas_d(w) = cas_d(w) + lambda(i,w);
        a(i,w) = lambda(i,w) / cas_d(w);
);
```

5.5 APPENDIX E: ACTUAL MONTHLY CASUALTY DEMAND

Casualty Location #		Scenario #							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Actual Monthly Casualty Demand (λ_{iw}) Emanating from each Casualty Demand Point per Scenario	1	2	1	1	1	1	1	1	1
	2	1	1	1	1	1	1	2	1
	3	2	1	1	1	1	2	1	1
	4	1	1	1	1	1	3	1	1
	5	1	1	1	2	2	1	1	1
	6	1	2	4	1	1	1	1	1
	7	1	1	1	1	2	1	1	2
	8	1	1	1	1	1	2	1	1
	9	1	1	1	1	1	1	3	1
	10	1	1	1	1	1	1	1	1
	11	1	1	3	1	1	1	1	1
	12	1	1	1	1	2	1	1	1
	13	1	1	1	1	2	1	1	1
	14	1	1	1	2	3	1	1	1
	15	1	1	1	1	1	1	1	1
	16	1	1	1	1	1	1	3	1
	17	1	1	1	3	1	1	1	1
	18	1	2	1	1	1	1	1	2
	19	2	1	1	1	1	1	1	2
	20	1	1	1	3	1	1	1	1
	21	2	1	1	1	1	1	1	1
	22	1	1	1	1	1	1	1	1
	23	1	1	1	2	1	1	1	1
	24	1	1	1	1	1	1	1	1
	25	1	1	1	1	1	1	1	1
	26	2	1	1	2	2	3	1	1
	27	1	1	1	1	1	1	1	1
	28	1	1	1	1	1	1	1	1
	29	1	1	1	1	1	1	1	1
	30	1	1	1	1	2	1	3	1
Total =		35	32	35	38	38	36	37	33

5.6 APPENDIX F: MAXIMUM PROBABILITY OF SUCCESSFUL EVACUATION

Casualty Location #		Scenario #							
		1	2	3	4	5	6	7	8
Maximum Probability of Successfully Evacuating Patients (P_{ijkw}) from each Casualty Location	1	100%	78%	100%	99%	100%	100%	0%	100%
	2	100%	39%	27%	100%	100%	100%	100%	2%
	3	100%	100%	0%	97%	99%	100%	100%	100%
	4	61%	100%	100%	60%	100%	100%	100%	100%
	5	98%	100%	100%	100%	100%	60%	100%	100%
	6	100%	100%	100%	100%	99%	100%	100%	100%
	7	97%	100%	100%	100%	100%	100%	100%	100%
	8	100%	100%	100%	100%	100%	100%	100%	42%
	9	99%	100%	100%	100%	100%	100%	100%	100%
	10	100%	100%	100%	100%	100%	94%	93%	90%
	11	100%	100%	100%	100%	100%	100%	100%	100%
	12	93%	100%	100%	96%	100%	100%	100%	70%
	13	100%	100%	100%	100%	100%	100%	88%	100%
	14	100%	100%	100%	99%	100%	100%	62%	100%
	15	100%	100%	100%	100%	100%	100%	100%	99%
	16	100%	100%	100%	52%	100%	100%	1%	100%
	17	89%	100%	24%	100%	100%	100%	100%	100%
	18	91%	100%	100%	100%	100%	100%	93%	100%
	19	100%	100%	100%	100%	100%	97%	66%	97%
	20	100%	100%	100%	100%	100%	100%	85%	100%
	21	100%	84%	100%	100%	100%	94%	100%	100%
	22	100%	100%	100%	100%	100%	100%	100%	100%
	23	100%	100%	100%	100%	91%	100%	100%	87%
	24	96%	100%	100%	100%	100%	100%	21%	100%
	25	100%	100%	100%	100%	100%	100%	100%	80%
	26	91%	95%	100%	100%	100%	100%	46%	100%
	27	100%	100%	94%	93%	100%	100%	100%	100%
	28	100%	99%	100%	27%	100%	100%	100%	100%
	29	100%	100%	100%	100%	100%	100%	100%	100%
	30	100%	100%	95%	100%	100%	100%	95%	100%

5.7 APPENDIX G: AVERAGE PROBABILITY OF SUCCESSFUL EVACUATION

Casualty Location #		Scenario #							
		1	2	3	4	5	6	7	8
Average Probability of Successfully Evacuating Patients (P_{ijkw}) from each Casualty Location	1	51%	47%	60%	66%	51%	57%	0%	100%
	2	74%	28%	11%	49%	46%	43%	100%	1%
	3	44%	100%	0%	96%	64%	100%	99%	64%
	4	58%	48%	100%	57%	54%	40%	100%	44%
	5	54%	73%	59%	61%	49%	36%	55%	75%
	6	77%	100%	100%	60%	60%	62%	100%	100%
	7	43%	44%	100%	100%	61%	52%	78%	100%
	8	76%	54%	75%	56%	61%	56%	55%	21%
	9	51%	51%	54%	56%	75%	66%	74%	54%
	10	74%	71%	42%	79%	51%	51%	88%	61%
	11	59%	99%	66%	72%	78%	74%	85%	63%
	12	49%	61%	100%	51%	60%	100%	100%	36%
	13	79%	100%	53%	70%	45%	44%	39%	36%
	14	99%	44%	49%	43%	52%	66%	61%	54%
	15	46%	60%	72%	45%	100%	75%	65%	42%
	16	54%	45%	80%	43%	46%	100%	1%	53%
	17	46%	100%	21%	61%	50%	55%	61%	82%
	18	40%	91%	51%	60%	100%	97%	90%	61%
	19	59%	44%	43%	79%	61%	48%	45%	52%
	20	51%	78%	40%	55%	61%	61%	28%	67%
	21	57%	27%	53%	53%	46%	59%	62%	76%
	22	76%	77%	58%	100%	43%	72%	66%	44%
	23	67%	100%	60%	100%	43%	100%	62%	86%
	24	59%	75%	61%	81%	68%	55%	18%	100%
	25	76%	100%	64%	71%	57%	75%	70%	43%
	26	68%	61%	78%	100%	76%	64%	40%	59%
	27	80%	100%	62%	57%	59%	68%	100%	67%
	28	77%	47%	59%	17%	51%	51%	47%	53%
	29	59%	52%	50%	64%	79%	76%	85%	58%
	30	49%	68%	51%	100%	81%	65%	48%	77%

5.8 APPENDIX H: GAMS PROGRAMMING CODE

```
$Title MEDEVAC Optimization Afghanistan Problem - Goal Programming Model
$Ontext
This work this work describes a strategic approach to optimizing the U.S. Army's
aeromedical evacuation system in Afghanistan.  Specifically, this work provides a robust,
multi-criteria, decision-analysis solution methodology using a scenario-based, stochastic goal
programming optimization model that U.S. Army medical planners can use as a strategic and
tactical MEDEVAC asset planning tool to engender a more effective Health Service Support
system in Operation Enduring Freedom.
$Offtext

*Seed for the random number generator
Option seed=100;
*Limits the amount of CPLEX solver time to 100,000 seconds
Option ResLim=100000;
*Limits the number of CPLEX solver iterations to 100,000 runs
Option IterLim=100000;

Sets
w scenarios                                                        /1*8/
i casualty demand locations                                        /1*30/
j feasible MEDEVAC_MTF helicopter emplacement sites                /E1*E21/
k aircraft model types                                             /K1, K2, K3/
s number of aircraft to be co-located at location 'j'              /2, 3, 4/
n number of U.S. Army Areas of Operation (AO) 'hotbeds'            /1*5/
xy xy pairs of coordinates                                         /X, Y/
t Monte Carlo simulation trials                                    /1*100/
fact factors involved in scenarios                  /occur, P1, P2, P3, casrad, vuln/;

Parameters
*Non-stochastic Components
dist_pu(i,j,k,w) distance between cluster 'i' and MEDEVAC_MTF site 'j' to pickup casualty
                 with aircraft 'k' in scenario w
mag(i,w)         radius around AO 'hotbed' for which casualties are likely to occur per scenario
a(i,w)           the proportion of demand originating in location 'i' such that the summation of
                 a(i) for all 'i' equals 1 for scenario w
c(k)             the number of aircraft model type k available in theatre
/
K1      2
K2      3
K3      12/

o(k)             the fleet operational readiness for aircraft model 'k' (percentage)
/
K1      0.667
K2      0.667
K3      0.667/
```

lit(k)		the number of litters available in aicraft type 'k'
/
K1 4
K2 4
K3 6/

p_comp		the probability of at least one available aircraft /.95/
td_min		triangular distribution minimum value (5 minutes in hours) /0.083/
td_max		triangular distribution maximum value (15 minutes in hours) /0.25/
td_most		triangular distribution most likely value (10 minutes in hours) /0.167/
thresh		the measure of effectiveness - successfully evacuation within 2 hours /2/
count		counter for the Monte Carlo Simulation to determine the number of successes
cas_d(w)	parameter used to calculate the total demand of all casualty locations in w
time_med	counter for the total time to MEDEVAC patient in the Monte Carlo simulation
evac_time(i,j,k,w) the Monte Carlo simulation average MEDEVAC time for 'i' to/from 'j' in w
max_P(i,w)	the Maximum Probability of MEDEVAC success at 'i' for each scenario w
vul_cap(j,w)	the vulnerability capacity for every facility 'j' in scenario w
en_attack(j)	the enemy capability lethality factor per MEDEVAC_MTF site 'j'
/
E1 1.014
E2 1.090
E3 1.025
E4 1.000
E5 1.154
E6 1.017
E7 1.017
E8 1.012
E9 1.012
E10 1.025
E11 1.025
E12 1.044
E13 1.047
E14 1.047
E15 1.000
E16 1.062
E17 1.005
E18 1.005
E19 1.009
E20 1.004
E21 1.009/

factors(w, fact) factors for each scenario in the model
totP		the total number of P greater than 0 per i and w
avg_P(i,w)	the average probability of successfully evacuating patients at i in scenario w

*Stochastic Components
vel(i,j,k,w,t)	helicopter transport velocity in trial t between MEDEVAC_MTF site 'j' and casualty location 'i' with aircraft 'k' in scenario w
ao(xy,n)	AO 'hotbed' NM grid coordinates in Afghanistan

```
cas(w,i,xy)       casualty location from AO 'hotbed' center of mass in scenario w
evac(j,xy)        coordinates for MEDEVAC helicopter emplacement sites
rand1(i,w)        random number used to determine casualty locations 'i' in scenario w
rand2(i,w)        random number used to determine number of casualties at 'i' in scenario w
rand3(i,j,k,w,t)  random number in trial t used for triangular distribution calculation in w
rand4(i,j,k,w,t)  random number in trial t used for triangular distribution calculation in w
rand5(i,j,k,w,t)  random number in trial t used for triangular distribution calculation in w
rand6(i,j,k,w,t)  random number in trial t used for triangular distribution calculation in w
rand7(i,j,k,w,t)  random number in trial t used for triangular distribution calculation in w
rand8(i,j,k,w,t)  random number in trial t used for triangular distribution calculation in w
rand9(j,w)        random number used for enemy attack probability in scenario w
casx(i,w)         random angle from AO center for which casualties are likely to occur in w
casy(i,w)         random angle from AO center for which casualties are likely to occur in w
leth(i,w)         lethality multiplier to model enemy capability uncertainty in scenario w
time_inj(i,j,k,w,t) the time in trial t from injury at the demand location to notification of
                  supporting MEDEVAC helicopter in scenario w
time_wup(i,j,k,w,t)  the time in trial t from notification to wheels up in scenario w
time_pup(i,j,k,w,t)   the time in trial t for flight time to pickup in scenario w
time_ld(i,j,k,w,t)      the time in trial t for patient load time at pickup location in scenario w
time_drop(i,j,k,w,t)  the time in trial t for flight time to medical treatment facility in w
time_offld(i,j,k,w,t)  the time in trial t for patient off-load time at the MTF in scenario w
trial(i,j,k,w,t)  the medevac time per trial t in scenario w
P(i,j,k,w)        the probability of successfully evacuating from casualty cluster 'i' in scenario
                  w with aircraft 'k' dispatched from closest location 'j' within the required 2
                  hour measure of effectiveness back to location 'j' in scenario w
r(j,k,s,w)        the maximum demand that can be supported from helicopter location 'j' in
                  scenario w with 's' number of aircraft type 'k' before necessitating 's+1' in w
lambda(i,w)       the actual demand emanating from casualty location 'i' in per month in w
vuln(j,w)         the vulnerability of the MEDEVAC_MTF site 'j' in scenario w
;

Table factors(w,fact)
        occur     P1     P2     P3     casrad     vuln
1       0.125     500    .2     .5     50.0       1.010
2       0.125     500    .2     .5     50.0       1.005
3       0.150     500    .2     .5     100.0      1.010
4       0.100     500    .2     .5     100.0      1.005
5       0.125     600    .6     .3     50.0       1.010
6       0.125     600    .6     .3     50.0       1.005
7       0.100     600    .6     .3     100.0      1.010
8       0.150     600    .6     .3     100.0      1.005
;

*Generate a random uniform seeds
rand1(i,w)=uniform(0,1);
rand2(i,w)=uniform(0,1);
rand3(i,j,k,w,t)=uniform(0,1);
rand4(i,j,k,w,t)=uniform(0,1);
rand5(i,j,k,w,t)=uniform(0,1);
```

```
rand6(i,j,k,w,t)=uniform(0,1);
rand7(i,j,k,w,t)=uniform(0,1);
rand8(i,j,k,w,t)=uniform(0,1);
rand9(j,w)=uniform(0,1);

*Assign the radius of casualties around each AO 'Hotbed'
mag(i,w)=uniform(-factors(w,'casrad'),factors(w,'casrad'));

*Setup AO 'Hotbed' Locations on the Grid
ao('X','1')=108; ao('Y','1')=189;
ao('X','2')=378; ao('Y','2')=162;
ao('X','3')=270; ao('Y','3')=162;
ao('X','4')=567; ao('Y','4')=324;
ao('X','5')=540; ao('Y','5')=243;

*Set up MEDEVAC/MTF site locations on the grid
*Sites support both hospital and evacuation assets
Table evac(j,xy)
        X       Y
E1      108     157
E2      162     157
E3      173     186
E4      224     173
E5      278     170
E6      113     256
E7      154     254
E8      197     327
E9      216     319
E10     243     221
E11     335     194
E12     432     162
E13     470     170
E14     486     208
E15     537     354
E16     440     221
E17     335     302
E18     286     337
E19     286     378
E20     297     424
E21     273     427
;

*casx/casy represent randomly generated angles up to 2*pi from the AO brigade
casx(i,w)=uniform(0,6.28);
casy(i,w)=uniform(0,6.28);
```

```
loop(w,
*Loop over all scenarios
loop(k,
*Loop over each aircraft type
        loop(j,
*Loop over each MEDEVAC/MTF asset location
                loop(i,
*Loop over each casualty demand location
                        if(rand1(i,w)<=.073,
                                cas(w,i,'X')=ao('X','1')+mag(i,w)*cos(casx(i,w));
                                cas(w,i,'Y')=ao('Y','1')+mag(i,w)*sin(casy(i,w));
                        elseif (rand1(i,w)<=.252),
                                cas(w,i,'X')=ao('X','2')+mag(i,w)*cos(casx(i,w));
                                cas(w,i,'Y')=ao('Y','2')+mag(i,w)*sin(casy(i,w));
                        elseif (rand1(i,w)<=.432),
                                cas(w,i,'X')=ao('X','3')+mag(i,w)*cos(casx(i,w));
                                cas(w,i,'Y')=ao('Y','3')+mag(i,w)*sin(casy(i,w));
                        elseif (rand1(i,w)<=.716),
                                cas(w,i,'X')=ao('X','4')+mag(i,w)*cos(casx(i,w));
                                cas(w,i,'Y')=ao('Y','4')+mag(i,w)*sin(casy(i,w));
                        else
                                cas(w,i,'X')=ao('X','5')+mag(i,w)*cos(casx(i,w));
                                cas(w,i,'Y')=ao('Y','5')+mag(i,w)*sin(casy(i,w));
                        );
                );

*Assign Distributions for the actual demand at each 'i' - number of casualties
                cas_d(w)=0;
                loop(i,
*Apply a lethality multiplier to the casualty generated at each location
*Evaluates sensitivity of location selection based on the number of injuries
*experienced on a site - and enemy capability uncertainty measure
                        leth(i,w)=uniform(1.0,1.154);

                        if(rand2(i,w)<=.874,
                                lambda(i,w)=round(1*leth(i,w));
                        elseif (rand2(i,w)<=.96),
                                lambda(i,w)=round(2*leth(i,w));
                        elseif (rand2(i,w)<=.99),
                                lambda(i,w)=round(3*leth(i,w));
                        else
                                lambda(i,w)=round(4*leth(i,w));
                        );
                        cas_d(w) = cas_d(w) + lambda(i,w);
                );
*Assign the proportion of demand originating in location 'i' such that
*the summation of a(i) for all 'i' equals 1 for each scenario w
                loop(i,
                        a(i,w)=lambda(i,w) / cas_d(w);
```

```
*Conduct a Monte Carlo Simulation with 100 trials
*Loop over t simulation MEDEVAC time trials
                    count=0;
                    time_med=0;
                    loop(t,

*Calculate the distances using Euclidean Distance Formula
                   dist_pu(i,j,k,w)=sqrt(sqr(cas(w,i,'X')-evac(j,'X'))+sqr(cas(w,i,'Y')-evac(j,'Y')));

*Stochastic Calculation of time_inj(i,j,k,w)
*Time from injury at the demand location to notification of supporting MEDEVAC aircraft
if((rand3(i,j,k,w,t)*(td_max-td_min)+td_min)>td_most,
      time_inj(i,j,k,w,t)=(td_most + (min(rand4(i,j,k,w,t),rand5(i,j,k,w,t))*(td_max-td_most)));
else
       time_inj(i,j,k,w,t)=(td_most - (min(rand4(i,j,k,w,t),rand5(i,j,k,w,t))*(td_most-td_min)));
);

*Stochastic Calculation of time_wup(i,j,k,w)
*The time from notification to wheels up
*Based on 2008 MEDEVAC AAR, mean time = 20-minute run up
*Thus, assume a normal distribution w/ mean=20 min stdDev=5 min (compute in hours)
                    time_wup(i,j,k,w,t)=normal(0.33,0.083);

*Uniform random distribution of the MEDEVAC helicopter speed
*from 120 to 193 Knots (NM/hour) depending on aircraft type 'k' and other random factors
                    vel(i,j,k,w,t)=uniform(120,193);

*Stochastic Calculation of time_pup(i,j,k,w) - the flight time to pickup
                   time_pup(i,j,k,w,t)=dist_pu(i,j,k,w)/vel(i,j,k,w,t);

*Stochastic Calculation of time_ld(i,j,k,w) - the patient load time at pickup location
if((rand6(i,j,k,w,t)*(td_max-td_min)+td_min)>td_most,
       time_ld(i,j,k,w,t)=(td_most + (min(rand7(i,j,k,w,t),rand8(i,j,k,w,t))*(td_max-td_most)));
else
       time_ld(i,j,k,w,t)=(td_most - (min(rand7(i,j,k,w,t),rand8(i,j,k,w,t))*(td_most-td_min)));
);

*Stochastic Calculation of time_drop(i,j,k,w) the flight time to medical treatment facility
*Assume the distance is the same to pick-up and drop-off patient because the same location 'j'
                    time_drop(i,j,k,w,t)=dist_pu(i,j,k,w)/vel(i,j,k,w,t);

*Stochastic Calculation of time_offld(i,j,k,w) the patient off-load time
*Based on the 2008 MEDEVAC AAR, they assumed a 5-minute off-load time
*Therefore, assume a normal distribution w/ mean =5 min stdDev=2 min
                    time_offld(i,j,k,w,t) = normal(0.083, 0.033);


                   trial(i,j,k,w,t)=time_inj(i,j,k,w,t)+time_wup(i,j,k,w,t)+time_pup(i,j,k,w,t)+
                                  time_ld(i,j,k,w,t)+time_drop(i,j,k,w,t)+time_offld(i,j,k,w,t);
```

```
                if (trial(i,j,k,w,t)<thresh,
                        count=count+1 ;
                else
                        count=count ;
                );

                time_med = time_med + trial(i,j,k,w,t);
*Close the 't' loop
                );

                 P(i,j,k,w)=count/card(t);
                 evac_time(i,j,k,w) = time_med/card(t);

*Close the 'i' loop
        );

*Calculating r(j,k,s,w) - the maximum demand that can be supported from helicopter location
        loop(s,
                r(j,k,s,w)=lit(k) * p_comp * o(k) * s.val;
*Close the 's' loop
        );

*Calculate vuln(j,w) - the vulnerability of the MEDEVAC_MTF site 'j'
*Equals the enemy capability lethality factor at 'j' x random uniform prob. of attack
                vuln(j,w) = en_attack(j)*rand9(j,w);

*Calculate the vulnerability capacity level for each facility 'j'
                 vul_cap(j,w) = factors(w, 'vuln');

*Close the 'j' loop
      );
*Close the 'k' loop
);
*Close the 'w' loop
);

Binary Variables
Y(i,j,k)        a binary variable for air evacuation assets, equals 1 if evacuation from location
                'i' with aircraft type 'k' dispatched from location 'j' is equal to or greater than
                pre-specified probability 'p' and 'j' is the nearest open location and facilities
                evacuation within 2 hours, 0 otherwise

X(j,k,s)        a binary variable for positioning of aircraft, equals 1 if 's' number of aircraft
                type 'k' are to be considered for positioning at location 'j', otherwise 0;

Positive Variables
dmin1(w)        the underachievment deviation for Goal 1
dplus2(j,k,w)   the overachievement deviations for Goal 2 for each 'j' and 'k'
```

dplus3(w)	the overachievemnt deviation for Goal 3
V	the value of the maximum vulnerability to be minimized
Q	the value of the maximum expected weighted scenario solution (**Model #2**);

Free Variable
z	the overall objective function cost to be minimized;

Equations
OBJFunc	define the overall goal programming objective function
G1	Goal 1 - Maximize the aggregate expected demands covered
G1_cp	Goal 1 - Coverage Probability Constraint
G2	Goal 2 - Minimize the spare capacities of air ambulances
G2_ap	Goal 2 - Aircraft Positioning Constraint
G2_aa	Goal 2 - Aircraft Available Constraint
G3	Goal 3 - Minimize the maximum vulnerability over the 'j' locations
G3_vul	Goal 3 - Vulnerability Capacity Constraint
G3_max	Goal 3 - Maximum Vulnerability Constraint
objf	the objective function constraint for Q (**Model #2**);

*--
* GOAL Program Equations
*--
G1(w)	.. sum((i,j,k), (a(i,w)*P(i,j,k,w)*Y(i,j,k))) + dmin1(w) =e= 1 ;
G2(j,k,w).. sum(s, r(j,k,s,w)*X(j,k,s)) - sum(i, lambda(i,w)*Y(i,j,k)) - dplus2(j,k,w) =e= 0 ;
G3(w)	.. V - dplus3(w) =e= 0 ;

*--
* Hard Constraints
*--
G1_cp(i)	.. sum((j,k), Y(i,j,k)) =l= 1 ;
G2_ap(j,k)	.. sum(s, X(j,k,s)) =l= 1 ;
G2_aa(k)	.. sum(s, s.val*sum(j, X(j,k,s))) =l= c(k) ;
G3_vul(j,w)	.. sum((i,k), vuln(j,w)*Y(i,j,k)) =l= vul_cap(j,w) ;
G3_max(j)	.. V =g= sum((w,i,k), vuln(j,w)*Y(i,j,k)) ;
objf(w)	.. Q =g= factors(w,'occur')*((factors(w,'P1')*dmin1(w)) +
	(factors(w,'P2')*sum((j,k), dplus2(j,k,w))) + (factors(w,'P3')*dplus3(w))) (**Model #2**);

*--
* Objective Function Formulation
*The three goals seek to emplace the minimum number of aircraft at each location 'j'
*necessary to maximize the coverage of the theatre-wide medevac demand
*and the probability of meeting that demand, while minimizing the maximal
*MTF site total vulnerability over the given set of scenarios
*--

OBJFunc.. z =e= sum(w,factors(w,'occur')*((factors(w,'P1')*dmin1(w)) +
(factors(w,'P2')*sum((j,k), dplus2(j,k,w))) + (factors(w,'P3')*dplus3(w))));

OBJFunc.. z =e= Q (**Model #2**);

```
*Setup the optimization model
model m /all/;
*Suppress the number of rows listed to 0
option limrow=0;
*Suppress the number of columns listed to 0
option limcol=0;
*Sets relative optimality tolerance - i.e. no tolerance because 0 = OPT value
option optcr=0;
*Solve the Mixed Integer Program model using CPLEX solver
m.OptFile = 1;
option MIP = Cplex;
SOLVE m using MIP minimizing z;

Parameters
*Calculate Casualty Statistics
emplace(j,xy)        the optimal emplacement of MTF evacuation sites over all scenarios
numcas_tot(w)        total number of casualties per month in scenario w
numevac(j,w)         number of casualties evacuated from casualty sites to_from site 'j' in w
numevac2(w)          total number of casualties evacuated in each scenario w
numevac3(j)          total number of casualties over all scenaries evacuated by 'j'
percevac(w)          percent of total number casualties that are evacuated in each scenario
tot_evac             total number of patients evacuated over all scenarios
percevac2(j)         percent of total number of evacuated casualted evacuated by 'j'
avgnumcas            average number of casualties per month over all scenarios
avgevac              average number of casualties evacuated per month over all scenarios
avgevac2(j)          the average number of casualties evacuated by 'j' per month over all
                     scenarios

*Calculate Helicopter Statistics
numhel(j,k)          the optimal # and positioning of type 'k' helicopters at site 'j'

*Calculate Distance, Speed and Time Statistics
totdist(i,j,w)       total distance traveled (in the month) to_from 'j' for evacuation of
                     patients at 'i' in scenario w
distj(j,w)           total distance traveled (in the month) to_from 'j' for evacuation of
                     patients in scenario w
time(i,j,k,w)        total MEDEVAC time (hours) to_from 'j' to evacuate patients at 'i' in w
time2(i,j,k,w)       time squared
ex2(w)               E(X^2) for time
exsquared(w)         (E(X))^2
avgdist(j)           average total distance traveled (in the month) to_from 'j' to evacuate
                     patients over all scenarios

*Calculate Sampling Statisitics
meandist(w)          mean distance traveled to_from an active 'j' in scenario w to evacuate
                     patients at a casualty site 'i'
speedall(w)          mean speed traveled to_from an active 'j' in scenario w to evacuate
                     patients at a casualty site 'i'
```

meantime(w)	mean time traveled to_from an active 'j' in scenario w to evacuate patients at a casualty site 'i'
avgtime	the overall average patient evacuation time
variance(w)	variance of time traveled for scenario w
std(w)	standard deviation of time traveled for scenario w
finalstderror	final standard error;

```
*Determine the Maximum Probability of Successful Evacuation of Casualties
max_P(i,w) = 0;
loop(j,
loop(k,
loop(i,
loop(w,
        if(P(i,j,k,w)> max_P(i,w),
                max_P(i,w) = P(i,j,k,w);
        else
                max_P(i,w) = max_P(i,w);
        );
); ); ); );

Display 'MONTE CARLO SIMULATION RESULTS',max_P;

*Determine the Average Probability of Successful Evacuation of Casualties
avg_P(i,w)=0;
loop(i,
loop(w,
        totP = 0;
        loop(j,
        loop(k,
                if(P(i,j,k,w)>0,
                        totP = totP + 1;
                );
        ); );

        avg_P(i,w) = sum((j,k), P(i,j,k,w))/totP;
); );

Display P, avg_P;

*Determine the Emplacement of MTF sites over all Scenarios
loop(j,
loop(xy,
        if(sum((i,k,w), Y.l(i,j,k))>0,
                emplace(j,'X') = evac(j,'X');
                emplace(j,'Y') = evac(j,'Y');
        );
); );
```

```
*Compute the Casualty and Helicopter Statistics
numcas_tot(w)         = sum(i, lambda(i,w));
numevac(j,w)          = sum((i,k), lambda(i,w)*Y.l(i,j,k));
numevac2(w)           = sum((i,j,k), lambda(i,w)*Y.l(i,j,k));
numevac3(j)           = sum((i,k,w), lambda(i,w)*Y.l(i,j,k));
percevac(w)           = numevac2(w)/numcas_tot(w);
tot_evac              = sum((i,j,k,w), lambda(i,w)*Y.l(i,j,k));
percevac2(j)          = numevac3(j)/tot_evac;
avgnumcas             = round(sum(w, numcas_tot(w))/card(w));
avgevac               = round(sum(w, numevac2(w))/card(w));
avgevac2(j)           = round(numevac3(j)/card(w));

*Compute the Helicopter Statistics
numhel(j,k)           = sum(s, s.val*X.l(j,k,s));

*Compute the Distance, Speed and Time Statistics
totdist(i,j,w)        = sum(k, Y.l(i,j,k)*dist_pu(i,j,k,w)*2)/lambda(i,w);
distj(j,w)            = sum(i, totdist(i,j,w));
avgdist(j)            = sum(w, distj(j,w))/card(w);
time(i,j,k,w)         = evac_time(i,j,k,w)*Y.l(i,j,k);
time2(i,j,k,w)        = power(time(i,j,k,w),2);
meandist(w)           = sum((i,j,k), Y.l(i,j,k)*(2*dist_pu(i,j,k,w)))/(sum((i,j,k),Y.l(i,j,k)));
speedall(w)           = sum((i,j,k,t),(vel(i,j,k,w,t)*Y.l(i,j,k)))/(sum((i,j,k),Y.l(i,j,k))*card(t));
meantime(w)           = meandist(w)/speedall(w);
avgtime               = sum(w,meantime(w))/card(w);

*Compute the Scenario Sampling Statistics
ex2(w)                = sum((i,j,k), time2(i,j,k,w))/card(w);
exsquared(w)          = meantime(w)**2;
variance(w)           = (ex2(w)-exsquared(w))/card(w);
std(w)                = sqrt(variance(w));
finalstderror         = sqrt(sum(w,exsquared(w))/card(w)-sum(w, meantime(w))/card(w))/
                        sqrt(sum((i,w),lambda(i,w)));

*Display the Locations of AO and MEDEVAC sites
Display ao, evac, emplace;

*Display of the Casualty Statistics
Display cas, lambda, numcas_tot, avgnumcas, numevac;
Display numevac2, avgevac, percevac, numevac3, percevac2, avgevac2;

*Display the Helicopter Type/Quantity Statistics
Display numhel;

*Display the Distance, Speed and Time Statistics
Display distj, avgdist, meandist, speedall, meantime, avgtime;

*Display the Scenario Sampling Statistics
Display ex2, exsquared, std, finalstderror;
```

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7 BIOGRAPHY

Nathaniel D. Bastian is a commissioned officer in the United States Army, where he serves as an Aeromedical Evacuation Officer in the Medical Service Corps branch. He earned a Bachelor of Science degree in Engineering Management with Honors from the United States Military Academy at West Point, and this work completes his requirements for a Master of Science degree in Econometrics and Operations Research from Maastricht University in The Netherlands. As a Fulbright U.S. Student Program Fellow in Engineering, his work and research has application to medical evacuation and ambulatory service optimization for systematic decision-making. He is a member of the American Society for Engineering Management, Military Operations Research Society, American Society for Engineering Education, and INFORMS.